On Modeling Future Workplace Location Decisions: An Analysis of Texas Employees

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ABSTRACT

In this paper, we examine work place location (WPL) preferences of workers in an unpredictable and evolving future by investigating how workers would prefer to allocate their monthly working days among the three WPL alternatives of working from home, from the work office, and from a variable third WPL. In contrast to earlier studies that typically focus on telework as a binary of whether an individual is a teleworker or not, we focus our attention on workers' preferences for specific combinations of all three WPLs over a period of a month (including, but not limited to, only selecting one WPL for all days of the month). In our analysis, we employ the multiple discrete-continuous extreme value (MDCEV) model, using a 2022 stated preference survey of future work preferences of employees residing in the state of Texas. The results indicate that single young women with very young children, those with long commutes and "intolerable" traffic congestion to the work office, individuals with a private study in their homes, self-employed workers, and those in non-essential service occupations have the highest preference for working from home. On the other hand, older men, individuals from low income households, those residing in rural areas, and workers in essential service occupations have the highest preference for the work office. And, for the third WPL, young non-single women with very young children, individuals from low income households, part-time employees, and those in professional, managerial or finance occupations have the highest predisposition. These results should provide valuable insights to urban planners, homebuilders, employers, travel demand modelers, and a whole host of other businesses to achieve specific desired end states. From a data collection standpoint, our study underscores the need to collect detailed information about work patterns in future activity-travel surveys.

Keywords: Work place location, teleworking, third work place, stated preference, work environment, hybrid work.

1. INTRODUCTION

Over the past two years, the COVID-19 pandemic has upended the routines and lifestyles of almost every person across the world, and workers have been no exception. While a small fraction of employees had flexible work arrangements before the pandemic, COVID-19 forced millions to shift into a virtual environment. With the initial stay-at-home orders in place, working from home became the norm. Remote work grew from roughly 7% worker participation in the US and 5% across Europe to about 62% in the US and 37% across Europe, respectively, through the first few waves of the pandemic in 2020 and 2021 (see DeSilver, 2020, Eurostat, 2020, Gallup, 2020, and Eurofound, 2020). A similar trend took hold throughout the globe. But as society started partially opening up in the later months of 2021 and into 2022, individuals have sought to revisit pre-COVID commute patterns, and are exploring a portfolio of work arrangements and workplace locations (WPLs).

In terms of WPLs, three possibilities (and their combinations) have become quite popular: the regular work place (the pre-COVID norm), the home (the post-COVID era norm), and a third workplace location such as coffee shops, designated co-working locations, hotels and restaurant (throughout this paper, we will use the label "Pre-COVID" to refer to the period *before the onset* of COVID in early 2020, and the term "Post-COVID" to refer to the period *after the onset* of COVID). Each of the three WPLs just listed has positive aspects as well as not-so-positive aspects in terms of social, personal and professional considerations (of course, what is positive and what is not-so-positive may itself vary across individuals). Thus, while working from home may be associated with a better work-family life balance for many individuals (Belostecinic et al., 2021), it also may be viewed as precluding the ability to socialize at the work place or reducing productive discussions as a unified team through face-to-face in-person conversations (Nash et al., 2021). Further, as in pre-COVID conditions, many employees may associate extended absences from the work place with a lack of visibility to management and potential career stagnation implications. On the other hand, commuting every day to the work place (as was the case for a large fraction of workers pre-COVID) may promote socialization opportunities and provide more visibility (Tahlyan et al., 2022 and Jaff and Hamsa, 2021), but can also be draining in terms of both financial considerations (for example, investment in clothing/attire and formal day care facilities for children; see Thompson et al., 2022 and Bjursell et al., 2021) and time/emotional considerations (for instance, long and tiresome commutes; see Nguyen, 2021). The third work place may appeal to some individuals because of fewer distractions and enriching small-scale socialization possibilities relative to working from home (Frick and Marx, 2021), while also eliminating a long commute and avoiding larger-scale gatherings at the usual work place (Egbuta et al., 2021). But this third workplace location arrangement may be expensive because of the need, for example, to rent hotel space (Nash et al., 2021); besides, it is still characterized by the decreased visibility associated with working away from the regular work place (Hermann and Paris, 2020).

It is clear from above that the three work location arrangements are not always perfect substitutes of each other, but may be better viewed as imperfect substitutes. Each location arrangement may satisfy specific functional, social, productivity, emotional, privacy, visibility,

networking, financial and other personal/professional objectives to different extents. As a consequence, it is likely that, given full choice of where to work from, many individuals will choose, over a certain period of time and within the context of their chosen/current career, a combination of these three WPLs to satisfy different personal and professional desires. Thus, unlike the plethora of studies before the pandemic that focused on whether an individual telecommuted from home at all or not over the course of a certain period of time (occasionally along with the frequency dimension of the number of days the individual works from home over the period of time), the emphasis moving forward needs to be on the mix of work locations sought after by individuals over a period of time, including not only home and the regular work location, but also possibly a third work location (this third work location may be a hotel day room near the home or even a constantly varying *digital nomadic* way of living/working on the move such as connecting from a ski resort or working from a beachfront; see Frick and Marx, 2021 and Nash et al., 2021).[1] At the same time, rather than employing statistical devices to tie the single discrete choice of telecommuting from home with the frequency of telecommuting, as in almost all pre-COVID studies, post-COVID decisions may be better characterized as a true utility-maximizing multiple discrete "horizontal" choice situation in which individuals balance the many pros and cons of each work location to determine an ideal mix of work locations over a certain duration of time.

The above discussion motivates the current study, which uses a multiple discrete-continuous model to determine the allocation of the monthly number of work days of an individual across three possible work location alternatives: (a) home, (b) regular work place, and (c) a third work place. Our analysis seeks to investigate this hybridization of the workplace location (WPL) in the emerging future where COVID becomes endemic -- that is, COVID effects are not as severe as in the early days of its onset, but still remain enough of a threat that safety prevention measures at different WPLs factor in the WPL decision-making of individuals (especially those who are themselves immuno-compromised or live with someone who is immune-compromised). Such an investigation of the "optimal" work location mix of employees can help guide transportation and land-use planning, and residential and commercial real-estate development, while also helping employers craft appropriate WPL policies that harness the full potential of their employee workforce in a way that is also consistent with employee desires. On this last issue, inadequate attention to employee WPL preferences can lead to dissonance between employee desires and employer WPL policies, which can further result in employees seeking other jobs.

To summarize, we apply a multiple discrete-continuous (MDC) model to identify the effects of sociodemographic characteristics, geographic and environmental attributes of each WPL alternative, job-related attributes, and COVID threat levels on employee WPL preferences. The discrete component here refers to whether an individual partakes in a specific work location

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[1] Though the term "digital nomad" existed before the pandemic, the label started receiving renewed attention after the COVID pandemic hit. While some studies define a digital nomad broadly as anyone who works at different places on a daily or weekly basis, other studies use a more specific characterization of the term for anyone who works remote and uses a digital device to connect to the regular workplace. In this study we will employ the first broader characterization.

arrangement at all or not, and the continuous component refers to the number of the work day instances in a month of each work location arrangement. The "budget" in the MDC model is exogenous and equal to the number of days of work per month. The study uses data from a 2022 Texas-based stated preference survey on commute and employment behavior in the fast approaching future of a COVID endemic state.

The rest of this paper is organized as follows. Section 2 provides a brief overview of past literature relevant to understanding the WPL decision. Section 3 presents the survey administration process, data preparation steps, and the analytic framework. Section 4 presents the model estimation results and goodness of fit measures. Section 5 discusses policy implications. Finally, Section 6 concludes the paper with a summary discussion, along with an identification of future research directions.

2. PREVIOUS LITERATURE

The global shift to remote and virtual environments during the "shutdown" period of the pandemic has accelerated the growth in literature dedicated to the study of telework. However, even pre-COVID, there was a healthy body of literature on the topic, though almost exclusively confined to working from home as the alternative to working from the regular work place (see, for example, Groen et al., 2018, Kaplan et al., 2018, and Silva-C et al., 2019 to identify just a few within the past five years). However, as discussed in the previous section, the WPL upheaval caused by the pandemic suggests a multiple discrete horizontal hybridization choice process at play in the post-COVID era. In this context, while there have been very recent studies (within the past two years) that investigate the kinds of WPL arrangements that may be most effective in the future, they do so more from a descriptive analysis standpoint or through the lens of what employees and employers view as positives and negatives of different WPLs (see, for example, Knoesen and Seymour, 2021, and Chamakiotis et al., 2021), rather than as a multiple discrete horizontal process of WPL preference formation. In this section, we will focus on post-COVID studies and also those that directly investigate employee-side teleworking-related processes and decisions (rather than those that confine attention to identifying the pros and cons of different WPLs, or those that examine personality attributes that are important for mental wellness when working remotely, or those that study the impacts of teleworking on wellbeing and health, or those that investigate job satisfaction levels of teleworkers). But we will also invoke pre-COVID studies as relevant for the purposes of our study. Our synthesis of previous investigations will be structured under four dimensions associated with teleworking, as identified by Haddad et al., 2009: *opportunity, preference, choice* and *frequency*.

2.1. Opportunity

The first dimension of *opportunity* refers to whether employers allow the possibility of teleworking in the first place (that is, whether employers officially sanction (with pay) the performance of work from a remote work place on one or more days over a period of a week or a month). Before COVID, in the US, teleworking allowance (that is allowance to work remote at any point in time) was at an

average of 50%-60% across all industries (Groen et al., 2018), though only about 20% of employees appeared to have embraced the opportunity (Parker et al., 2020). The opportunity/allowance for teleworking increased during the pandemic, and currently almost 80% of employers allow their employees to telework (Tokarchuk et al., 2021), with over 70% of employees availing of the opportunity, even if only occasionally (Parker et al., 2020). Earlier studies on opportunity fall under two broad categories: (a) employer perceptions of teleworking and (b) the types of jobs/occupation sectors that typically allow teleworking. In the first broad category of employer perceptions, many pre-COVID studies suggested managerial skepticism about allowing teleworking, much of which revolved around mistrust of employees' use of time (see Peters et al., 2004 and Kaplan et al., 2018), lack of in-person communication amongst a team of employees (see Beham et al., 2015, and Peters et al., 2004), and the manager's reluctance to invest in change (see Silva-C et al., 2019 and Egbuta et al., 2021). But after companies were forced to move their companies into a virtual mode during the pandemic, it appears that attitudes have shifted. Specifically, most of the recent literature has found that, by investing in more digital technology (Athanasiadou and Theriou, 2021) and by recognizing the benefits teleworking brings to their employees (Chamakiotis et al., 2021, Tokarchuk et al., 2021), managers appear more comfortable in providing a work-from-home or hybrid work location option into the future (Belostecinic et al., 2021). In the second broad category of jobs/occupation sectors more likely to allow teleworking, Groen et al. (2018) found that 69% of employees at financial service institutions were allowed to telework, compared to 16% for public administration positions. Similarly, Cetrulo et al. (2020) found low levels of remote working allowance for blue collar workers (0% of plant and machine operators, only 0.5% of crafts, agriculture and specialized workers and 5% of service and sale workers were allowed to telework), as compared to the white-collar workers, with over 50% allowance to work remotely (71.5% of clerical workers, 57% of technical professionals, 58% of intellectual and scientific workers, and 61% of legislators, managers and entrepreneurs).

A limitation of these earlier studies is they do not adequately consider an employee perspective. Two recent studies following the COVID-19 pandemic (Sheather and Slattery, 2021 and Hopkins and Figaro, 2021) suggest that a new period of the "great resignation" has fallen upon us, and that employers and managers need to start being more sensitive to employee needs to develop customized WPL opportunity policies to retain their workforce. The current study examines employee desires, while indirectly considering an employer perspective too by investigating how employees themselves filter the reality of the needs of their occupation sector/job type when developing their optimal WPL desires.

2.2. Preference and Choice

The *preference* and *choice* dimension are intricately linked, with the former focusing on the process (perspectives toward teleworking if the opportunity is available) and the latter representing the actual manifested decision. Because of the close overlap of the two dimensions, our synthesis of the literature will simultaneously examine both these dimensions. Much of the earlier literature

along these dimensions focus on sociodemographic factors impacting WPL preference/choice, while there is also some literature on job-related and location-related effects. On the former sociodemographic factors, studies, for the most part, have consistently found that women, younger workers, employees with children, married employees, and higher educated individuals have a higher teleworking preference and are more likely to choose to telework relative to other individuals. But Zhang et al. (2020), while reviewing these earlier studies, point out occasional inconsistencies in the studies for the effect of gender, presence children, and married employees. They conjecture that these differences may be because earlier studies have not adequately considered the interaction effects of sociodemographics, especially the three-way interaction of gender, marital status and parenthood (in their terminology, "gendered family-life stage"). Their study uses multiple telework theories of teleworking preference to position earlier empirical results, and suggests that telework preference will increase as individuals attempt to reduce work-to-family (WTF) conflict (work interfering with family) at the cost of increasing family-to-work (FTW) conflict (family interfering with work). Based on these theoretical conflict constructs, they note that, while employees with children are more likely to telework irrespective of gender and marital status, single individuals without children are more likely to telework than non-single individuals without children, and men without children are more likely than women without children to telework. But, for individuals with children, non-single parents are more likely to telework than single parents, and women are more likely to telework than men. In summary, the Zhang et al. study notes that the presence of children changes the effects of gender and marital status, and sociodemographic interaction effects with the presence of children is important in explaining telework propensity. Accordingly, in this study, we consider a number of possible multi-way interaction effects of sociodemographics, not only among themselves but also with environment and location-related effects. Related to job-related and location-related effects, earlier studies have generally found that part-time workers, those residing far away from their regular work location, those residing in high density urban areas, those who live closer to non-work and leisure activity opportunities, and those working in small-sized firms tend to telework more than other individuals (see, for example, Zhang et al., 2020 and Caldarola and Sorrell, 2022).

Most of the preference/choice studies identified above use revealed preference studies of pre-COVID teleworking choice or "at present" teleworking choice in the midst of the pandemic. Only three studies, to our knowledge have focused on WPL desires in the more distant future using stated preference data. Nayak and Pandit (2021) and Jain et al. (2022) study an employee's intention to telework based on a direct question regarding stated intent in a future when "travel and other restrictions would be withdrawn after the elimination or control of the pandemic" (Nayak and Pandit) or the virus is "gone" (Jain et al., 2022). Specifically, Nayak and Pandit elicit a binary response to whether the employee would be willing to telework in the future, while Jain et al. pose a question related to how much more likely (as collected on a seven-point Likert scale) would the respondent be to telework in the future compared to pre-COVID times. The results from these studies indicate that highly educated individuals, those from small-sized households, younger individuals, women with children, married women, and those whose coworkers also telework

indicate a higher willingness to telework in the future, as do individuals in occupation sectors other than service and sales. Commute time did not affect stated teleworking adoption. But these studies did not consider work environment attributes (such as noise and crowdedness) and COVID threat.

The third study by Appel-Meulenbroek (AM) et al. (2022) is the closest in spirit to the current study, and so will be discussed in more detail. As in our current paper, this study analyzes the results from a stated choice experiment. Also, as in the current paper that asks individuals to provide their ideal preferred WPL choice, AM et al. ask respondents to assume that working from home is allowed as a free choice each day. In their experiment, a respondent is asked to choose their preferred discrete WPL choice during a specified day from among three varying in-person workplace alternatives and one "work from home" alternative. The in-person work alternatives are characterized by work environment attributes (noise, openness, space size, crowdedness, concentration spaces, communication spaces, and positioning workplace in relation to walking route) and work activity day type (communication work day type with unplanned meetings and relatively little concentrated individual desk time; concentrated work day type with few unplanned meetings and high intensity of concentrated individual desk time; and a 50/50 work day type of the hybrid of the first two). The results underscore the importance of work environment characteristics that have received little attention in the literature. In particular, crowdedness and noise were important in deciding whether to telework or not, while openness of the office layout had no effect. Employees did not like workspace surrounded by regular intelligible conversations and/or a busy floor where almost all surrounding desks are occupied.

Overall, while close in spirit to the current paper, our research is also quite different from that of AM et al. paper. While AM et al. consider a single day as the analysis frame, we investigate individual desires for working from different WPLs over a period of a month. Also, the AM et al. study assumes zero effect of COVID moving forward (respondents were asked to assume that the COVID-19 pandemic will no longer affect the work situation in the office), while we believe a more reasonable assumption would be that COVID would still be a threat at least for some individuals (such as immuno-compromised individuals). Besides, the AM et al. study does not consider the frequency dimension of teleworking.

2.3. Frequency

This dimension reflects how many times employees telework within a temporal period, such as a week, month, or year. Some of the studies that consider this dimension consider zero frequency as part of the frequency range (see, for example, Beck et al., 2020), while a few consider telework adoption (telework at least once) separately from telework frequency and use statistical stitching mechanisms to jointly model adoption with frequency (Popuri and Bhat, 2003, Sener and Bhat, 2011, and Shabanpour et al., 2018). There have been many pre-COVID studies focusing on this frequency dimension (see, for example, e Silva and Melo, 2018, and Shabanpour et al., 2018) as well as several post-COVID studies (see, for example, Zhang et al., 2020, Hensher et al., 2021, Heiden et al., 2021, Jain et al., 2022). The pre-COVID studies predominantly focus on demographic and job-related factors influencing teleworking frequency. But the pandemic has

disrupted work configurations, and has led to a wholesale rethinking of priorities and desires among employees (see Smite et al., 2022). And most of the post-COVID studies attempt to investigate the immediate "at present" change in telework frequency brought about by COVID (using revealed preference data). These studies tend to use an aggregate level of analysis (rather than an individual-level of analysis), and use a single teleworking variable to capture both telework adoption and frequency. Besides, a few of these "at present" teleworking studies do not model the actual count of teleworking days, but consider frequency in ordinal categories (such as working remote "Always", "Several times per week", "Several times a month", "Less than once per month", and finally "Never", for did not work at home at all; see Shabanpour et al., 2018 and Heiden et al., 2021). And the three post-COVID studies that examine possible trends into a more distant future (see previous section), using stated intentions data, model only telework adoption and not telework frequency too. Further, all earlier studies consider a binary distinction between regular work place and a remote work place (with most explicitly considering the remote work place as home), and do not consider a third WPL as a possible alternative.

2.4. Current Paper in Context

In the current paper, we build on past literature in multiple ways. <u>First</u>, we examine WPL choices and corresponding frequencies from the perspective of a unified (across choice and frequency) utility-based horizontal choice optimal arousal theory[2]. That is, in the WPL context, an employee will choose the optimal combination of WPL frequencies across their days of work over a period of time (a month in this paper). <u>Second</u>, we consider three possible WPL locations; Home, an established in-person work office (which we will refer to henceforth simply as work office), and a third work place (such as a hotel or a coffee shop). In doing so, we examine the characteristics of "digital nomads". <u>Third</u>, we recognize that the desired WPL choice combination over a month will be impacted by a comprehensive combination of three distinct sets of attributes associated with work location and job characteristics: (1) the geographic attributes of the alternative WPL locations, (2) the environment attributes of each of the alternative WPL locations, and (3) job-related attributes. *Geographic WPL attributes* refer to such "external" characteristics of the location as commute time to the non-home WPL locations, congestion levels during the commute, and the built environment characteristics around the location (captured, admittedly, in a simple but important way through a density classification scheme of locations). *Environment WPL attributes*, on the other hand, refer to such "internal" characteristics of the location such as distraction level, crowding level, and socialization opportunities and access. We also include, for the first time to our knowledge, two home-related attributes within the environmental WPL set of attributes, including the tenure type of the house (renting versus owning) and the presence of a study/office at home. *Job-related attributes* include number of work days per month, employment status (full time or part-time), employment structure (self-employed versus non-self-employed), occupation sector, and the ability to shift work hours over the course of the day. As discussed earlier, some of

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[2] Optimal arousal is a psychological construct representing the level of mental stimulation and personal satisfaction at which physical performance, learning, or feelings of wellbeing are maximized and balanced (Smith 1990).

these job-related attributes proxy employer-provided opportunity effects by investigating how employees themselves filter the reality of the needs of their respective jobs when developing optimal WPL desires. Fourth, we do consider COVID threat levels, and how this may impact WPL choices in general, and particularly for specific segments of the population. Fifth, in addition to including the many attributes identified above, we also consider multi-way interactions among these attributes using a sample size of 1,136 individuals, each of whom provides responses to two stated preference questions for a total of 2,272 choice occasions for analysis. As Zhang et al. (2020) indicate, earlier studies have been rather limited in investigating interaction effects, at least in part because of the small sample sizes available for analysis. Sixth, from a methodological standpoint, we explicitly accommodate covariances across the baseline utilities of the different WPL alternatives as well as consider panel effects (unobserved individual effects that permeate across the two stated preference choice occasions of the same individual; ignoring such effects can lead to an underestimation of standard errors and potentially incorrect inferences about the statistical significance of the parameter estimates). Finally, a majority of the published post-COVID telework studies are at non-US locations and/or focus on current telework (from home) choice. In this paper, we examine the desired WPL state of individuals into the future using survey data collected from the State of Texas in the US.

3. METHODOLOGY

3.1. The Survey

The primary data for the current study is drawn from a workplace location (WPL) choice survey deployed across Texas, US in February-March 2022, coordinated through efforts with the Texas Department of Transportation (TxDOT). The survey administration approach included an array of communication and information recruitment strategies, including promotion via e-mail to several chambers of commerce across the state of Texas, alongside other businesses, professional organizations, and media outlets, as well as a database of roughly 55,000 Texas residents' email addresses. Survey access was restricted to individuals who were employed/students, who were residents of the state of Texas at the time of the survey. Of the 1,450 responses from the target population (workers/students), 304 individuals did not respond to commute and current workplace-related questions and/or did not adequately respond to the SP experiments that formed the main outcome variable in the analysis. The resulting sample of 1,146 respondents had 10 students who were not employed, who were then removed to retain a final sample of 1,136 employed individuals (and 1,136×2 = 2,272 choice occasions). All these individuals had a work office at the time of the survey (even if they never commuted to that location). The survey was deployed at a time when the Omicron variant was past its peak in Texas, and there were absolutely no COVID-related restrictions and safety measures in place in Texas. In fact, Texas had lifted all COVID-related mandates/restrictions as early as March 2021 (Office of the Texas Governor, 2021). The survey collected information on pre-COVID, during the worst of COVID, and current work patterns. In addition, socio-demographics (age, gender, employment type, education level, household annual

income, and number of children in a household) and the current work office/home location information was obtained.

For this analysis, the focus, as in Appel-Meulenbroek et al. (2022), is the response to the stated preference questions regarding desired WPL state at a future time, though when COVID still would be present in an endemic state and enough of a threat to warrant some level of consideration. Pre-COVID or current WPL choices would not represent this future desired state well because these earlier/current actual choices are likely to have been constrained by employer allowance/opportunity and other general safety restrictions because of the pandemic.[3] Besides, as discussed earlier, motivations and priorities are likely to have changed because of the pandemic. Thus, in this analysis, we do not use these current WPL choices to explain future desired WPL states, though we do use current work office geographic attributes and job characteristics (including sector of work, employee's perspective of how easy it is to have work be undertaken remotely, part time versus full time work status, urban/suburban/rural location of the work office, and perceived congestion levels to the work office) to explain future desired WPL state. The implicit assumption here is that individuals will generally stay in their current occupations and work arrangements into the not-too-distant future, even if their desired future WPL state may (and generally will) be quite different from pre-COVID or current WPL choice.[4]

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[3] This position is supported by Jain et al. (2022). As they indicate, while the transtheoretical model (TTM) of behavior change (Prochaska and DiClemente, 1982) suggests that long term continuation of a behavior is more likely among those who earlier contemplated making the behavioral change (working remotely in our case), they provide empirical evidence to suggest that COVID-related lockdowns were like forced 'experiments' related to WPL choice that are not necessarily indicators of long-term desires or actual behavior. Further, on the issue of our use of stated preference data (in our case, the stated preference of work location configuration in an environment where individuals have full freedom to choose), it is well established that behavioral preferences/intentions precede behavioral action. In fact, this fundamental concept is at the foundation of the Theory of Planned Behavior (TPB; Ajzen, 1991) and the traditional Technology Acceptance Model (TAM) (Davis, 1989; Venkatesh and Davis, 2000). Extensive studies in the social-psychology, information sciences, and consumer behavior literature have also validated the strong and unambiguous relationship between self-reported preferences/intentions to pursue a certain behavior and the actual future action (even if in an uncertain future environment, and even if not perfect, and particularly for studying causal relationships; see, for example, Marikyan et al., 2019, Gunden et al., 2020, and Bernheim et al., 2022).

[4] Employment studies generally note that individuals are likely to stay in the same general profession even if they change jobs (see, for example, Gebbels et al., 2020, Bauer et al., 2020, Dauth et al., 2017). As discussed earlier, these current profession-related characteristics serve the purpose of being a proxy for the level of telework opportunity likely to be available to the employee's job, and that may influence the future desired WPL state. While there is potentially more fluidity in part-time versus full-time decisions and the physical work office location over time, we implicitly assume that these characteristics (along with the current home location, home tenure, and presence study/office at home) will remain relatively unchanged in the not-too-distant future (because these are not used as separate attributes in the SP experiment, but are derived from the current home/work information provided by the respondent). In this regard, while the period of the great resignation started in 2020 and is far from over, it appears to have peaked in April 2021 (Verma and Banerjee, 2022). In 2022 and beyond, a period of the "great resignation u-turn" or "the great regret of the great resignation" or "the boomerang employee" (Marks, 2022, Stillman, 2022, Davidson, 2022, Upadhyay, 2022, Tong, 2022) has also come upon us, wherein many employees are rejoining the same company (and the same sector) from which they earlier resigned. Of course, we also admit that there continues to be uncertainty in these work temporal trends post-COVID, an issue that calls for some caution in the interpretations and insights from the current study and other earlier related post-COVID studies discussed in Sections 2.2 and 2.3. However, as we will note soon, we do use commute time itself as an attribute in the SP experiment, to engender more variation (due to varying traffic congestion levels) in this attribute as we study the effect of the attribute on desired

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In the SP part of the survey, each respondent was presented two scenarios and asked to allocate their total number of working days per month across the three different WPL alternatives: (1) home, (2) work office, and (3) third WPL[5]. For example, in response to a specific scenario of attributes, a full-time worker employed 22 days in a month may split things up as five days from the work office, 15 days from home, and two days from a third WPL. The attributes used in each scenario include commute times to the work office and third WPL, measures of distraction and crowding level for different work locations, flexibility of work hours (both the permission to shift working start time and to split up hours across the day), and COVID-19 risk intensities associated with each possible location. The attributes and their respective levels are presented in Table 1, along with a sample SP WPL question in Figure 1. Different from typical SP choice experiments (see, for example, Hensher et al., 2021) that elicit a single choice response (as also undertaken by AM et al., 2022), we use a horizontal choice structure approach to elicit responses where the respondent decides an optimal combination of allocation of the total number of work days across the three WPL locations. The attribute levels (for the experiment) themselves were designed with the intention to keep the scenarios realistic, while engendering good variability in the attribute values across scenarios. In all, there were 23,040 possible combinations of the attribute levels. From these combinations, a fractional factorial design selected 40 different scenarios with the emphasis on isolating main effects and, to some limited extent, two-way and higher-order interaction effects. It is clearly infeasible to present 40 SP choice questions to each respondent, and hence we used the randomization feature in the survey design software Qualtrics to randomly assign two of the 40 SP questions to each respondent. The randomization feature automatically monitors the frequency of presentation of each of the 40 questions to respondents, in order to evenly pace and distribute every one of the 40 questions throughout the entire sample of responses.

3.2. Sample Description

We are unable to compare the individual-level demographic characteristics with the Census Bureau data or the five-year American Community Survey, because these latter databases do not distinguish between employed and non-employed individuals. But, in terms of geographic WPL attributes and job characteristics, we are able to compare our sample statistics with those drawn from the 2020 Texas Census (Texas Demographic Center, 2022). Our sample slightly overrepresents the self-employed population in Texas (16.8% of the sample relative to 7% self-employed in Texas as identified in the 2020 Texas Census). On the other hand, our sample underrepresents part-time employees (6.6% as compared with 11.4% of the Texas population). But our sample is pretty representative of industry types. Also, in terms of commute times, the average one-way commute time in Texas is 26.4 minutes, while our sample's average commute time is

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future WPL state. Similarly, we also use work time flexibility as an SP experiment attribute, allowing some work characteristics to be specified into the future rather than being held to the current state.

[5] Respondents were reminded multiple times throughout the survey that an in-person work office includes: their company's office or worksite, their school's building or campus, or a client's site. The third workplace was also repeatedly defined as locations such as a coffee shop, a designated co-working space, a hotel, or a restaurant, but does not include working from a client's site, which would instead be categorized as an in-person workplace.

25.2 minutes. Similarly, the average number of days an employee works in a month is 22 days, and our sample reported working an average of 21.5 days. Additionally, before COVID, about 5% of Texans worked from home every day, while 9.3% reported doing so to in our sample. These numbers increase to 22% and 19.4%, respectively, when considering if an employee worked from home at least once a week. Additionally, about 50% in our sample never worked remotely pre-COVID, which is close to the 47% in the population that never worked remotely. The above statistics do suggest that our sample reasonably represents characteristics of the employed population in Texas; the desired WPL status in the future as expressed in our sample may be considered a good reflection of the future WPL desires of the Texas employed population as a whole. We include a detailed table of the sample's descriptive statistics in an online supplement (available at https://www.caee.utexas.edu/prof/bhat/ABSTRACTS/WPLSP/OnlineSupp.pdf).

In terms of the main outcome variable of analysis, as previously mentioned, there are two dimensions (or components) related to WPL choice: a discrete component associated with whether an individual desires to partake in a specific work location arrangement at all or not (the preference dimension), and a continuous component referring to the number of work day instances of each WPL alternative if that WPL alternative has positive participation.[6] Table 2 provides the descriptive statistics of the discrete and continuous components across the 2,272 choice occasions. The second and third columns indicate the number (percentage) of occasions involving the choice of each WPL alternative and the mean number of days of participation conditional on positive participation in each WPL, respectively. Two observations may be made from the statistics in these two columns. First, the home and work office alternatives are about equally chosen with close to about 70% participation, while the third WPL location is less likely to be chosen at only 14.5%. Second, conditional on each of the home and work office locations being selected as options, each of these alternatives has a mean number of days of participation of about 14.5 days per month. On the other hand, the third WPL location, even when chosen, has a mean number of days of participation of about 7 days. These suggest an overall high baseline preference (high discrete participation) and relatively low satiation effect (high participation intensity) for the home and work office WPLs, and an overall low baseline preference (low discrete participation) and high satiation effect (low participation intensity) for the third WPL.

The last broad column of Table 2 provides the split among the four possible WPL combinations for each WPL alternative. Thus, the numbers in the second row indicate that, of the 1635 choice occasions in which "Home" is chosen as a WPL location, 599 occasions (36.6% of 1635) involve only the "Home" as the selected WPL location over the entire monthly period of employment, while 771 occasions (47.2% of 1635) involve a mix of days of working from home

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[6] The "continuous" quantity used in our model is actually a count variable, as opposed to a truly continuous measure as required by the multiple discrete-continuous (MDC) model (see Section 3.3). But, as demonstrated by von Haefen and Phaneuf (2003), treating the integer count of work days as a continuous variable (within an MDC framework) does not lead to substantial bias in the results or the behavioral implications. Indeed, this result has been the basis for the use of the MDC model in the transportation, tourism, and recreational fields that analyze recreational/leisure trips to multiple destinations (where trips represent counts). Examples of such studies include Van Nostrand et al. (2013) and Kuriyama et al. (2020).

and work office, 83 occasions (5.1% of 1635) involve a mix of days of working from home and a third WPL, and 182 (11.1% of 1685) involve a mix of days of working from all three of the WPLs. The numbers in the subsequent two rows can be similarly interpreted. These numbers clearly indicate that WPL stated choices over a period of a month is a multiple discrete situation, with close to 47.2% of the occasions involving the choice of a hybrid of WPLs rather than a single WPL to work from (a total of 599+572+29=1200 occasions or 52.8% of the 2,272 occasions involve the choice of a single WPL on all days of work; 26.3% of the occasions involve working only from home; the corresponding percentages for work office and third WPL are 25.1% and 1.4%, respectively). Also, the splits across the different WPL combinations when each of the home and work offices are chosen as an alternative are quite similar (see the numbers in the second and third rows), except that it is more likely that the combination of home and a third WPL is chosen than the combination of work office and a third WPL. Additionally, the last row of Table 2 indicates that the third WPL is much less likely to be participated in as the sole location for work across all days of employment over the month (this occurs only 8.8% of the time when WPL is chosen as an alternative). Basically, the third WPL is most likely to be participated in within a hybrid combination of all three WPLs together (this happens in 55.2% of occasions when the third WPL is chosen as an alternative; see the last row and last column of Table 2).

Across all the 2,272 choice occasions, the mean number of days of participation in each of the three WPLs are as follows: home (10.5), work office (10.0), and third WPL (1.0), totaling up to the mean number of 21.5 work days per month in the sample.

3.3. Modeling Framework

In this paper, a panel version of the mixed multiple discrete-continuous extreme value (MMDCEV) model (see Bhat, 2008, Spissu et al., 2009) is implemented to analyze individual's monthly split of workplace location choices in the following three categories: (1) Work from home, (2) Work from in-person work office, and (3) Work from a third work place. The model was estimated using libraries and routines written by the research team in the GAUSS matrix programming language (Aptech, 2022).

The model formulation accommodates heterogeneity (*i.e.*, differences in behavior) across individuals due to both observed and unobserved individual attributes while considering the panel structure. In the following presentation of the panel MMDCEV model structure, the index q (q = 1, 2, …, Q) is used to denote individuals, t (t = 1, 2, …, T) for the choice occasions, and k (k = 1, 2, …, K) for workplace location alternatives. Let $\boldsymbol{x}_{qt} = \{x_{qt1}, x_{qt2}, ..., x_{qtK}\}$ be the vector denoting the number of days chosen by individual q for the workplace location k during choice occasion t. Using these notational preliminaries, the structure of the monthly distribution of workplace location days model for panel (or repeated choice) data is discussed below.

Consider the following additive utility functional form:

$$U_{qt}(\boldsymbol{x}_{qt}) = \sum_{k=1}^{K} \gamma_{qtk} \ \psi_{qtk} \ \ln\left(\frac{x_{qtk}}{\gamma_{qtk}} + 1\right). \tag{1}$$

In the above utility function, $U_{qt}(x_{qt})$ refers to the utility accrued to the individual due to the chosen horizontal monthly distribution x_{qt} of the workplace location days for choice occasion t. The term ψ_{qtk} refers to the baseline preference of the three alternative workplace locations and controls the discrete choice participation decision in the alternative k (k = 1, 2, 3, …, K) for individual q at choice occasion t. The term γ_{qtk} ($\gamma_{qtk} > 0$) is a translation parameter that serves to allow corner solutions (zero selection) for the alternatives as well as allow differential satiation effects across these alternatives, with values of γ_{qtk} closer to zero implying higher satiation (or lower number of days selection for a particular workplace) for a given level of baseline preference (see Bhat, 2008 for details). To complete the model specification, the baseline parameter for the three workplace alternatives are given by

$$\psi_{qtk} = \exp(\theta_k + \boldsymbol{\beta}' z_{qk} + \boldsymbol{\mu}_q' s_k + \boldsymbol{\eta}_q' w_k + \varepsilon_{qtk}). \tag{2}$$

The terms in the baseline parameter expression for the alternatives in Equation (2) are as follows. The <u>first term</u> θ_k is a constant that denotes the "average" (across individuals) effect of unobserved variables on the baseline utility associated with workplace k. The <u>second component</u> $\boldsymbol{\beta}' z_{qk}$ accounts for the impacts of individual specific attributes as well as alternative attributes on the choice decision. In this component, $\boldsymbol{\beta}$ is a vector of coefficients, and z_{qk} is a vector of observed attributes specific to individual q and alternative k. The <u>third component</u> $\boldsymbol{\mu}_q' s_k$ represents individual q's differential preference for the alternative k across the choice occasions compared to the other alternatives, thereby capturing the panel effects embedded in the model structure. In this component, s_k is a column vector of dimension K with each row representing an alternative (the row corresponding to alternative k takes a value of 1 and all other rows take a value of 0), and the vector $\boldsymbol{\mu}_q$ is a $K \times 1$-column vector with each element $\mu_{qk} \sim N(0, \sigma_k^2)$. The reader will note here that the $\boldsymbol{\mu}_q$ vectors take the same value for all observations (or choice occasions) of a given individual. This generates correlations across the choice occasions of a given individual, capturing the panel effect. The <u>fourth component</u> $\boldsymbol{\eta}_q' w_k$ constitutes the mechanism to generate individual level correlation across unobserved utility components of the alternatives. In this component, w_k is specified to be a column vector of dimension H with each row representing a group h (h = 1, 2, …, H) of alternatives sharing common individual-specific unobserved components (the row(s) corresponding to the group(s) of which k is a member take(s) a value of one and other rows take a value of zero; *i.e.*, w_{hk} =1 if k belongs to group h and 0 otherwise), and the vector $\boldsymbol{\eta}_q$ (of dimension H) may be specified as a H-dimensional realization from a multivariate normally distributed random vector $\boldsymbol{\eta}$, each of whose elements have a variance of ω_h^2. The elements of $\boldsymbol{\eta}$ are assumed to be independent of each other, and the realization vector for any individual is independent of the

realization vector of other individuals. The result is a variance of $\sum_h w_{hk}\omega_h^2$ across individuals in the utility of alternative k with an associated covariance between alternatives k and l of $\sum_h w_{hk}w_{hl}\omega_h^2$. Thus, this fourth component captures heterogeneity due to unobserved attributes that are correlated across alternatives. The <u>fifth term</u> ε_{qtk} is an idiosyncratic choice-occasion specific term for individual q and alternative k, assumed to be identically and independently standard type I extreme-value distributed across individuals, alternatives (activity purposes), and choice occasions (with a fixed scale).

Let $\boldsymbol{\theta}$ be a vector of the θ_k elements; $\boldsymbol{\gamma}$ be a vector of the γ_{qtk} elements, $\boldsymbol{\sigma}$ be a vector of parameters characterizing the σ_k^2 elements, and $\boldsymbol{\omega}$ be a vector of parameters characterizing the ω_h^2 elements. The parameters to be estimated in the panel MMDCEV model include the $\boldsymbol{\theta}, \boldsymbol{\beta}, \boldsymbol{\gamma}$, $\boldsymbol{\sigma}$ and $\boldsymbol{\omega}$ vectors. For given values of $\boldsymbol{\mu}_q$ and $\boldsymbol{\eta}_q$, the probability of the observed workplace location distribution of days $x_{qt}^* = \{x_{qt1}^*, x_{qt2}^*, ..., x_{qtK}^*\}$ of individual q at choice occasion t is given by (Bhat, 2008):

$$P(x_{qt}^*, \boldsymbol{\theta}, \boldsymbol{\gamma}, \boldsymbol{\beta}) \mid (\boldsymbol{\mu}_q, \boldsymbol{\eta}_q) = \left[\prod_{k=1}^{M} c_{qtk}\right]\left[\sum_{k=1}^{M}\frac{1}{c_{qtk}}\right]\left[\frac{\prod_{k=1}^{M} e^{V_{qtk}}}{\left(\sum_{k=1}^{K} e^{V_{qtk}}\right)^M}\right](M_{qt}-1)!, \text{ where}$$ (3)

M_{qt} = the number of alternatives chosen by individual q at choice occasion t,

$$c_{qtk} = \left(\frac{1}{x_{qtk}^* + \gamma_{qtk}}\right) \text{ for } k = 1, 2, 3, ..., M,$$

$$V_{qtk} = \theta_k + \boldsymbol{\beta}' z_{qk} + \boldsymbol{\mu}_q' s_k + \boldsymbol{\eta}_q' w_k - \ln\left(\frac{x_{qtk}^*}{\gamma_{qtk}}+1\right) \quad (k = 1, 2, 3, ..., K).$$

To develop the likelihood function for parameter estimation, the probability of each sample individual's set of observed workplace location days' distribution is needed. Conditional on $\boldsymbol{\mu}_q$ and $\boldsymbol{\eta}_q$, the likelihood function for individual q's observed set of time investments is:

$$L_q(\boldsymbol{\theta}, \boldsymbol{\gamma}, \boldsymbol{\beta}) \mid (\boldsymbol{\mu}_q, \boldsymbol{\eta}_q) = \prod_{t=1}^{T_q}\left[P(x_{qt}^*, \boldsymbol{\theta}, \boldsymbol{\gamma}, \boldsymbol{\beta}) \mid (\boldsymbol{\mu}_q, \boldsymbol{\eta}_q)\right].$$ (4)

The unconditional likelihood function for individual q's observed set of choices is:

$$L_q(\boldsymbol{\theta}, \boldsymbol{\gamma}, \boldsymbol{\beta}, \boldsymbol{\omega}, \boldsymbol{\sigma}) = \int_{\boldsymbol{\eta}}\int_{\boldsymbol{\mu}}\left[L_q(\boldsymbol{\theta}, \boldsymbol{\gamma}, \boldsymbol{\beta}) \mid (\boldsymbol{\eta}, \boldsymbol{\mu})\right]dF(\boldsymbol{\eta} \mid \boldsymbol{\omega})dF(\boldsymbol{\mu} \mid \boldsymbol{\sigma}).$$ (5)

The log-likelihood function is:

$$L(\boldsymbol{\theta},\boldsymbol{\gamma},\boldsymbol{\beta},\boldsymbol{\omega},\boldsymbol{\sigma}) = \sum_q \ln[L_q(\boldsymbol{\theta},\boldsymbol{\gamma},\boldsymbol{\beta},\boldsymbol{\omega},\boldsymbol{\sigma})], \qquad\qquad\qquad (6)$$

where $\boldsymbol{F}$ is the multivariate cumulative normal distribution. The reader will note that the dimensionality of the integration in the above expression depends on the number of elements in $\boldsymbol{\mu}$ and $\boldsymbol{\eta}$. Simulation techniques are applied to approximate the multidimensional integral in Equation (6), and the resulting simulated log-likelihood function is maximized using a scrambled Halton sequence method (see Bhat, 2003).

4. MODEL RESULTS

During the modeling specification process, we pursued a systematic (and elaborate) process of considering several functional forms and combinations of explanatory variables, while eliminating statistically insignificant ones. Individual demographic and household characteristics such as respondent age, respondent's household income, and presence of children by age (which were collected in categorical form as opposed to in a continuous form), as well as work characteristics (such as occupation type and perceived commute congestion levels), were tested as dummy variables in the most disaggregate form collected, and gradually combined based on statistical tests to yield parsimonious specifications. Similarly, continuous variables (such as number of days worked per month, population density, and employment density) were tested in their linear form as well as non-linear dummy variable forms. Except for one explanatory variable (commute time), the non-linear dummy variable form outperformed the linear form in terms of data fit.

A few other points about our specification. First, to accommodate heterogeneity across individuals in the effect of observed variables not only in the baseline preference function (the ψ_{qtk} function as in Equation (2)), but also in the satiation parameters (the γ_{qtk} parameters), we parameterized the satiation parameters as $\exp(\boldsymbol{\delta}_k'\boldsymbol{\omega}_{qt})$, where $\boldsymbol{\omega}_{qt}$ is a vector of independent variable characteristics and $\boldsymbol{\delta}_k$ is a vector to be estimated (note that $\gamma_{qtk} > 0 \ \forall k$). This allows the discrete choice decision of choosing a specific WPL to be less closely tied to the continuous intensity choice of the fraction of days of investment in that WPL (see Bhat, 2008). Second, we used a t-statistic threshold of 1.00 to retain variables (corresponding to a 0.32 level of significance or 68% confidence level), because of the moderate-sized sample used in the analysis, the small share of individuals who use the third workplace location, and the potential for such included variables to guide future WPL investigations with larger sample sizes. Third, while we attempted a host of different interaction effects, only those related to gendered lifecycle (interaction of gender with presence of children and household structure) turned up as being important. For example, we attempted interactions related to age and being immunocompromised with COVID risk (to test the notion that older individuals and those immunocompromised would be more concerned about high COVID risk levels relative to other individuals). But these and other interaction effects did not even turn up marginally significant in our specifications. Fourth, while we tested race and ethnicity effects, these effects turned out to be statistically insignificant at even the 0.32 level of significance after controlling for income effects and occupation effects. When these other effects were not

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added, those who were non-Hispanic White were more likely to work from home or a third work place relative to their peers of other race/ethnicity groups (Ray and Ong, 2020).

The model results for the effects of variables on the logarithm of the baseline preference (that is, the effects of variables on $\ln(\psi_k)$, or the elements of the $\boldsymbol{\beta}$ and $\boldsymbol{\theta}$ vectors) are presented in the next section, while the effects of variables on the logarithm of the γ_k parameters (that is, the elements of the $\boldsymbol{\delta}_k$ vector) are presented in the subsequent section.

4.1. Baseline Preference Parameter Estimates

Table 3 presents the model results. In instances where some variables have no effect on a specific WPL alternative (denoted by a "—" in the table), the corresponding alternatives constitute the base category in introducing the variable's effect. The results are discussed below by five categories of variables: individual and household demographics, geographic WPL attributes, environment WPL attributes, job-related attributes, and general COVID threat levels.

Individual and Household Demographics
Several observations may be made based on the effects of the variables corresponding to gender, presence of children, and living with or without a partner. *First*, in general, in a consumer-driven future WPL situation, women express a lower preference than men for the work office relative to working remotely (from home or a third WPL). Earlier studies have observed that men generally prefer the work office because they view the office as a primary social outlet (while women tend to socialize much more outside work with non-coworkers; Bilodeau et al., 2020) as well as a way to position themselves for professional advancement (Greguletz et al., 2019). On the other hand, women appear less likely to even seek promotions because of the additional work pressures and responsibilities of upper management positions (Georgiadou and Syed, 2021). *Second*, the results also show that the preference for work at home is highest for women with young children (0 to 4 years of age) not living with a partner (most likely these individuals would be single mothers). Single mothers tend to be particularly financially challenged, and being able to work from home can save money; besides, working from home can also provide more interaction time with their children as the only parent (Schieman et al., 2021). *Third*, women with young children 4 years of age or younger living with a partner have a heightened preference for a third WPL relative to all other individuals. Women, in general, still tend to shoulder much of the responsibility of child-care even when with a partner (Nguyen, 2021). Thus, to be productive, they may prefer a non-distracted "away-from-home" location for their work hours when there is some form of support for child care from the partner. Interestingly, and consistent with women continuing to shoulder much of the responsibility for child care, the presence of young children does not have any impact on men's WPL preferences. *Fourth*, the result related to "lives with a partner", while appearing simple, also has a gendered lifecycle nature to it. Specifically, except for the case of women with young children 0 to 4 years of age living with a partner, men, and women with no young children 0 to 4 years of age and who live with a partner, are the least likely to express an interest in a third WPL. The preference for a third WPL is somewhere in-between for individuals who are not living

with a partner. These results may be attributed to the fact that, when in a couple relationship, men, and women with no young children 0 to 4 years of age, are less likely to seek a digital nomadic lifestyle (Thompson, 2019) (as already indicated, the exception of women with children 0 to 4 years of age living with a partner bucks this tendency because the third WPL may be a recourse to getting some productive work time when there is a partner to help). *Finally*, in the context of household structure effects, workers with children aged 13 to 17 years (regardless of gender and living arrangement) have a higher preference to work from a third workplace (but not the work office) compared to those without children in the 13-17 years age group. This may suggest a general preference to continue staying close to home at a third WPL rather than commute to work when there are teenage children, but also an attempt to seek a calmer and more productive environment than at home (Nayak and Pandit, 2021). Overall, our results support those of Zhang et al. that "gendered family-life stage" effects do exist in the context of sociodemographic determinants of WPL choice.

In terms of age, not surprisingly, older workers are more likely to work from their work office relative to their younger peers, and the oldest cohort of workers (over 65 years of age) are particularly unlikely to work from a third workplace. The human development literature indicates that older individuals are likely to resist change and stick to life rhythms that they have been used to, in part because they perceive change as a loss of control that leads to anxiety and stress (Duque et al., 2019). Thus, being accustomed to the work office setup (and the socialization, professional visibility and structure associated with a work office), these older workers are likely to have viewed the pandemic and stay-at-home work orders as merely temporary restrictions, rather than opening up alternative WPL doors and opportunities. On the other hand, younger individuals seek control and freedom over both work and play hours, which is facilitated by working remotely (Asdecker, 2022). Besides, social and emotional interaction networks have been known to differ between younger and older adults. While younger adults strive to have expansive social-professional networks in and outside of their work environment (including stronger desires for a "digital nomadic lifestyle"), older adults prefer small and familiar social-professional networks such as those at their work office (Tahlyan et al., 2022).

Finally, in the group of individual and household-level demographics, Table 3 indicates that employees making over $100,000 a year express a lower baseline preference to work from the work office than those making $100,000 a year or less. This aligns with most past literature (see for example, Tahlyan et al., 2022). Typically, with more money comes more freedom, including the freedom to choose to work remote (Yasenov, 2020). Furthermore, those who are making less than $100,000 may make concerted efforts to climb the professional ladder. Though ideally earned through merit, many workers perceive that promotions are bolstered by in-person workplace visibility (Jaff and Hamsa, 2021). In addition to the lower baseline preference for the work office, those who make more than $250,000 a year are significantly less likely to work from a third workplace.

Geographic WPL Attributes

Geographic WPL attributes refer to "external" characteristics of the location, including travel-related attributes to the WPL (commute time and perceived level of congestion) and built environment characteristics of the location of the WPL. In the SP experiments, the commute time variable to the work office was specified as a percentage of the current commute time to the work office (note that the term "current" here refers to the commute time to the current physical location of the work office, regardless of whether the respondent is currently commuting at all or not). The specific attribute level for the commute time variable at each SP choice occasion, as indicated in Table 1, was picked from "75% shorter than current", "50% shorter than current", "same as current", "50% longer than current", and "75% longer than current". For the third WPL, the commute time for each choice occasion was picked from "shorter than current commute to the work office" and "same as current commute time to the work office". For the analysis, we assumed the first of these levels as referring to "50% shorter than current commute to the work office". With these percentages based off the current commute time to the work office (which was collected in the survey), we constructed the effective commute times to the work office and the third WPL corresponding to each choice occasion as a continuous variable.

The perceived level of congestion on the commute was collected only for the work office, separate from the SP choice experiment, by asking respondents to provide their level of agreement to the following statement "There is too much congestion during my commute to or from work". The response was collected on a five-point Likert scale: "strongly disagree", "somewhat disagree", "neutral", "somewhat agree", and "strongly disagree". In the analysis, responses in the last two of these ordinal categories were labeled as "intolerable" congestion, while the remaining were classified as "tolerable" congestion.

In terms of the built environment characteristics, respondents self-classified their home residential location area into one of rural, suburban, or urban categories. Respondents were also asked to provide the zip code of their work office, which was then mapped to a categorical classification of "low", "medium", or "high" density characterization of the work office location.[7]

The results in Table 3 for the geographic WPL attributes indicate the expected negative effect of commute time on WPL preference, with this negative effect being particularly elevated for women relative to men. Indeed, the appeal of not having to commute has been long established as one of the main reasons for preferring to work at home. Further, after two years of no commute due to lockdowns, it appears that many individuals who would never have considered remote work from home or a third office before have also more explicitly experienced the time savings from having a reduced or no commute at all, thus raising awareness levels about the opportunity cost of commuting. That this opportunity cost of commuting should be elevated for women is no surprise because of the generally time-poor nature of working women (who continue to shoulder much of

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[7] This density characterization was obtained by mapping the work zip codes to census block groups (CBGs), appending CBG employment density (the total number of jobs per unprotected acre) based on the U.S. EPA Smart Location Database (see Ramsey and Bell, 2014), and then classifying, based again on Ramsey and Bell, CBGs with an employment density less than 2.2 as "low" employment density, and those with employment densities higher than 5.2 as "high"; all other work locations are classified as "medium" density.

household work, especially when in a partnership), though this effect may also be due to societal influences/pressures and/or other gender-related reasons. The results in Table 3 also reveal the strong negative effect of an "intolerable" congestion level during the commute to the work office on the work office preference.

The built environment effects in Table 3 reflect the disinclination for the work office when the work office is located in a high density neighborhood and/or when the residence of the respondent is located in an urban or suburban area (with the negative effect being stronger for urban residences). This may be attributed to the travel time unreliability that usually accompanies commutes originating from and/or destined to high density areas (Foucault and Galasso, 2020), but also attributable to high parking-related expenses in such areas. Besides, it has been well established in the literature that those living or working in low density areas intrinsically appear to be less likely to work from home, as the regular work office environment serves as a particularly important socialization outlet in such communities (see Castrillon et al., 2020). Table 3 also shows a negative preference effect of urban/suburban living on the third WPL alternative, presumably for similar reasons as for the negative preference effect of urban/suburban living on the work office.

Environment WPL Attributes

Before moving on to a discussion of the environmental WPL attributes, first some definitional issues. For the work office and third WPL, our survey attempted to characterize distraction levels using a four-level categorization of a combination of crowding and noise levels (see Table 1): (1) "no crowding, no noise", (2) "some crowding, some noise", "(3) "crowding, no noise", and (4) "crowding, high noise". But, in all our specifications, we could not distinguish between the effects of the first and second categories above (this result is actually consistent with AM et al. who observed that office-goers were not very sensitive to low levels of crowdedness and calmness relative to no crowding at all). So, in our final specification, we translated the four-level categorization for the work office and third WPL into three levels: (1) Low distraction (that is, a combination of "no crowding, no noise" and "some crowding, some noise"), (2) medium distraction (that is, "crowding, no noise"), and (3) high distraction ("crowding, high noise").

Now to the results. Table 3 reveals that medium distraction levels (relative to low distraction levels) at the home and third WPLs do decrease the preference, respectively, for the home and third WPL alternatives, and high distraction levels at these two WPLs decrease the preference for these two WPLs even more than for medium distraction levels. Interestingly, though, the elevated effect of the high distraction level compared to the medium distraction level is tempered for workers over the age of 30 years for the home location. In particular, note that the baseline preference coefficient for workers younger than 30 years in a high distraction home setting (relative to a low distraction home setting) is -0.702, while the corresponding effect for workers over 30 years is -0.365 (= -0.702 + 0.337). Next, the results for distraction levels at the work office are interesting, and are dependent on the gender and age of the worker. For men younger than 30 years of age, medium distraction levels (relative to low distraction levels) do lead to a decrease in work office baseline preference, but not so for men 30 years or older. The effect of distraction

between the medium and high levels does not affect the baseline preference for the work office differentially for men younger than 30 years, while the high level does "kick in" to reduce the work office preference for those 30 years or older. For women, regardless of age, and regardless of medium or high distraction levels, there is a higher reduction in work office preference relative to men. In summary, for the work office, it appears that young men (<30 years of age) are more sensitive to distraction levels compared to men 30 years or older, and women are more sensitive than men to distraction levels (regardless of age). This result reinforces earlier results for age and gender that suggest that the work office serves as an important social-professional venue particularly for older adults and men relative to younger adults and women, respectively.

Table 3 also indicates the influence of housing-related attributes, with individuals owning their home having a higher baseline preference for the work office than those renting, and those with a private study in the home having a higher preference for working from home compared to those without a private study. The former result deserves more probing in future efforts, while the latter may be explained by both the productivity as well as the convenience appeal of a non-distracting private study environment (Wöhrmann and Ebner, 2021).

__Job-Related Attributes__
The extent, status, structure, and type of work an employee is involved in influences WPL preferences, though these effects may also be the effect of what the job demands. The effect of the number of days worked per month was tested originally as a continuous variable, but the final form of this attribute was several incremental dummy variables. The pattern of coefficient effects corresponding to this variable suggests a higher preference for work hybridization (that is, working from multiple WPLs during the month) as the number of work days increases (note that the coefficient values move closer and closer to being equal across the three WPLs as the number of work days increase). In particular, there appears to be a lower baseline preference for working outside home for those who work fewer days per month, but this effect fades as the number of work days in the month increases. In addition to the number of work days, part-time employees have a higher baseline preference than full-time employees for a third WPL.[8] Given that we have already controlled for the number of work days, this part-time effect may be viewed as a part-day work effect (that is, corresponding to individuals who work only a few hours per day). Thus, the preference for a third WPL here may be a reflection of the WPL flexibility inherent in part-time positions, or because individuals who seek out part-time employment are those who prefer work

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[8] An interesting note here. A majority of the individuals, 990 out of 1136 (87%) to be precise, indicated that they worked full-time (30 or more hours per week) and worked 20 days or more per month. This would be a rather traditional work arrangement. However, of the 74 individuals who worked part-time (<30 hours per week), 28 (38%) indicated that they worked 20 days or more per month. Similarly, 72 individuals who indicated they work full-time also reported working less than 20 days per month. These observations suggest that full-time versus part-time work refers more to the intensity of work hours during the days worked, and is not necessarily perfectly correlated with the number of days of work. This is another reason that future studies on work patterns must focus on longer-term periods such as a month rather than on a single day or even a single week – a part-time worker may be working all working days of the week, though less than the traditional 8 hours per day. And a full-time worker may not be working all regular weekdays of the month, but working full days on the days worked.

portability and a digital nomadic work style (Su et al., 2021). The results in Table 3 also reveal that those who are self-employed (but who indicated that they have a regular work place outside home, because that was a screening criterion in the survey) have a lower baseline preference for the work office than those not self-employed, as has been found in the earlier literature too, suggesting more control over work arrangements (Cheng et al., 2022).

In the category of job-related variables, occupations that generally may be viewed as "essential" for day-to-day workings of society, such as healthcare and food service workers, as well as retail sales, education and social service employees, have a high baseline preference for the work office or a low baseline preference for remote work (Astroza et al., 2020) relative to those that may be considered non-essential (professional, managerial, and technical jobs). Workers in the public administration have the lowest preference for the work office, while those in information/finance have a clear higher preference for working from home or a third work place.

Finally, another job-related characteristic investigated was whether an employer allowed shifting work hours to either an earlier or later start/end time. The results suggest that women are more predisposed toward the third WPL in this situation, perhaps taking advantage of the temporal flexibility to reinforce their tendency to work away from (but close to) home. A similar reason presumably underlies the higher preference to work remotely among those with children.

COVID-19 Threat

If immunocompromised, an employee is less willing to work from the work office, a natural protective measure to avoid being around coworkers or strangers who may be infected or not taking COVID precautions (see Irawan et al., 2022). Many states have recognized this basic health-driven tendency by enacting policies, such as Colorado's Safer at Home public health order, which shields immunocompromised workers from having to return to the work office (Harold et al., 2022). Of course, the same reasoning also applies to the result pertaining to the case when an individual visits or lives with someone who is immunocompromised.

The COVID risk attribute was represented in the experiments at one of four levels (see Table 1 for details): extremely low, low, unknown, and high. In our specifications, there was consistently no difference in the extremely and low COVID risk levels (these two risk levels corresponded to 60% or 80% vaccinated, "with the vaccine being effective for all strands"). This suggests that individuals are not very sensitive in the range of vaccination penetrations we presented. Combined with the important effects of high risk and unknown risk, which included the dimension of the vaccination's effectiveness being poor or unknown, respectively, there is an indication that the public is swayed more by vaccination effectiveness information than vaccination penetration levels in the population. For the final model specification, we combined the extremely low and low risk levels into a single "not high" risk level, with "high" and "unknown" being separate levels.

The observation from Table 3 is that if the COVID risk is high at any time, the baseline preference for working from home increases, as one would expect (see Baba et al., 2022). What is interesting in our results is that if the COVID risk is uncertain, the baseline preference for working

from home increases even more than when the COVID risk is known to be high. However, as we will note later, if the COVID risk is high, those individuals working from home decide to do so with much more intensity, while there is no such effect of "unknown risk" on the frequency of working from home for these individuals. That is, while "unknown risk" increases the likelihood of working from home at least once more so than "high" risk", "high risk" increases the frequency of working from home more so than "unknown" risk". Of course, which of "high" risk and "unknown risk" increases the split of days working from home will be a combination of these two, which can only be determined through the type of predictions undertaken in Section 5. The positive coefficient on the "unknown risk" variable for the work office lies between the preference coefficients for home and the third WPL, which suggests that the preference for a third WPL declines the most when the COVID risk is uncertain, perhaps because individuals at a third WPL are much more likely to be strangers (than at home or at the work office) with unfamiliar safety behaviors, especially when the COVID risk is unknown with no safety protocols in place.

Baseline Preference Constants
The baseline constants do not have any substantive behavioral interpretation. They work with the satiation preference constants to provide the best data fit, after accommodating the effects of exogenous variables. But, it is illustrative to note the negative coefficient on the third WPL alternative even after including exogenous variable effects. This, as discussed in Table 2, the satiation constant for the third WPL is the lowest. This is in congruence with the lowest participation rate in the third WPL, based on the descriptive statistics in Table 2.

4.2. Satiation Effects
As indicated earlier, the satiation parameter is parameterized as $\exp(\delta_k' \omega_{qt})$, and the results in the lower panel of Table 3 represent the elements of the coefficient vector δ_k. A positive coefficient has the effect of increasing the γ_k parameter and, thereby, reducing satiation effects (increasing days of work for the WPL alternative k, conditional on participation in the WPL alternative k), while a negative coefficient has the effect of decreasing the γ_k parameter and increasing satiation effects (decreasing days of work at the WPL alternative k, conditional on participation in the WPL alternative k). Important also to note is that the satiation effects begin to take effect from the baseline parameter as the starting point (the baseline parameter may be viewed as the marginal utility of an alternative when no days have yet to be invested in that WPL alternative; see Bhat, 2008). Thus, the net WPL package choice prediction for an individual (that is, the number of days of work for each WPL alternative (and all WPL alternatives), given the total number of days of work of the individual), is a function of the combination of the baseline parameters and the satiation parameters across all WPL alternatives for that individual.

Individual and Household Demographics

As in the case of the baseline parameters, "gendered family-life stage" effects and age continue to play an important role in determining intensity of participation in each WPL, conditional on participation in the WPL alternative. For women with children below the age of 13 years in the household and living with a partner, the intensity of work participation at the work office is lower than for all other individuals, even if there is some positive participation at the work office. However, the reverse is true for women with children between the ages of 13-17 years in the household and living with a partner. Of course, we can attribute this effect primarily to the gender and presence of children combination here, given that single mothers with young children are unlikely to participate in the work office in the first place (see the discussion of the baseline preference effects in the previous section). Young children demand a significant amount of attention, and women are the primary caregivers even in families with a partner (especially in the majority of cases, at least today, where the other partner identifies as being a non-female). So it is only intuitive that women with children, even if they travel to the work office on some days, would not do so too often during the month. On the other hand, women in households with older children 13-17 years of age, if they work from the work office at all, may feel more comfortable doing so with reasonably higher intensity than women in households with young children, given the generally more independent biological and activity rhythms of teenagers.

The age effects on satiation reinforce the notion that older adults (especially those 65 years of age or older) prefer stability and regular rhythms in their lifestyle. Specifically, given a specific WPL is chosen for participation, older workers are generally more likely than younger workers to maintain that WPL for frequent participation, while younger adults generically prefer a more hybrid location work environment.

The results related to household income effects on satiation reveal that individuals from households with an annual incomes of $100,000 or higher, while having a higher baseline preference to work remotely than those from households with incomes less than $100,000, still are more likely to distribute their work days across multiple WPLs (note the negative effects of "income $\geq$ 100,000" on the two remote WPL alternatives), presumably another sign of the flexibility and power higher income households wield in the market place.

Geographic WPL and Environmental WPL Attributes

An interesting finding from Table 3 is that geographic and environmental WPL variables do not differentially impact the intensity of participation in any of the three WPL alternatives, conditional on participation. That is, the effects of these attributes on participation and the intensity of participation in each WPL is determined solely through their effect on the baseline preference of each WPL combined with the generic satiation constants for each WPL (discussed later).

Job-Related Attributes

The only job-related structure affecting satiation in any statistically significant way is the employment structure. Specifically, self-employed individuals, while having a lower baseline

preference for the work office, do not necessarily travel less frequently (than those not self-employed) on a monthly basis to the work office, conditional on working from the work office at least once during the month. The reader will note that the baseline preference for the work office is low for self-employed individuals relative to not self-employed individuals; so satiation effects begin from an already low baseline preference point for these individuals, and, by having a smaller satiation effect for the self-employed individuals, the model ensures that self-employed individuals are not assigned a very low frequency of working from the work office subject to positive work participation from the work office. This may be explained based on the nature of work for some self-employed individuals. For example, a self-employed lawyer may have to go into office to meet up with clients, regardless of whether they prefer their in-person workplace over their remote ones.

COVID-19 Threat
The satiation results related to COVID threats indicate that when an individual frequently visits another person who is immunocompromised, not only is the individual less likely to have a work participation instance at the work office, but also go in fewer times to the work office even if there is a work office participation instance at all. Clearly, this is another indication of the general worry of being COVID messengers to individuals who may have serious reactions to the virus. Similarly, when the COVID risk is high, individuals not only are likely to prefer the home office as their WPL, but also work for a high number of their work days from the home office. This is clearly an effective prevention approach to reduce COVID exposure.

Satiation Constants
As in the case of the baseline preference constants, the satiation constants do not have any substantive interpretation. They work with the baseline preference constants to provide the best fit to the data, after accommodating the effects of exogenous variables. But, as discussed in Table 2, the satiation constant for the third WPL is the lowest, consistent with the highest satiation observed from the descriptive statistics in Table 2 for the third WPL.

4.3. Panel and Covariance Effects
The final model also explicitly accommodates panel effects (that is, common unobserved individual characteristics that permeate into the baseline preferences for each WPL alternative across the two choice occasions from the same individual) as well as covariances across the baseline utilities of the different WPL alternatives (using an error-components structure at the choice occasion level, as discussed in Section 3.3). With three alternatives and two choice occasions, a maximum of four parameters are estimable (these can include three panel effects, one each for each alternative, and one pairwise error-component; see Bhat, 2008 and Walker et al., 2004). However, it can become difficult to estimate all the four parameters empirically, as also observed by Walker et al. in a general mixing estimation context. In our modeling, we attempted to estimate all the four parameters, but encountered some instability. So, we decided to estimate

two panel effects (for two of the three alternatives) and one inter-alternative covariance effect in the baseline utilities. Alternative specifications for this three-parameter model were estimated. The best specification was obtained when (a) the panel effect for the home alternative was normalized to zero (this was the alternative with the lowest variance in unobserved factors across individuals), and the other two panel effects were estimated, and (b) the covariance between the work office and third WPL was left free to be estimated. Specifically, the variance across individuals in unobserved factors affecting the work office and third WPL baseline utilities are estimated to be 0.296 (t-statistic of 1.49) and 0.218 (t-statistics of 1.57), respectively. These values indicate that the variation across individuals (due to unobserved factors) is highest for the work office and lowest for the home office, and somewhere in-between for the third work place. The variance of the common error term generating the covariance between the work office and third work place is estimated as 0.055 (t-statistic of 0.75), which is clearly not statistically significant. The implication is that there are no common unobserved factors affecting the three WPL alternatives, conditional on the exogenous variables, in our empirical context.

4.4. Model Goodness of Fit

The performance of the panel MMDCEV model may be compared with that of a constants-only model (in which we only allow constants in the baseline preferences and in the satiation parameters of the alternatives). Since the panel and constants-only models are nested forms of one another, their performances can be compared using the likelihood ratio test. The log-likelihood at convergence for our panel model is -6740.25, compared to the constants-only log-likelihood value of -7113.62. A likelihood ratio test yields a value of 746.74, which is much higher than the chi-squared table value with 63 degrees of freedom at any reasonable level of significance (there are 68 parameters in our model, compared to five parameters in the constants-only model).

Our panel model and the constants only model may also be compared using a predictive Bayesian Information Criterion (BIC) statistic $[= -\mathscr{L}(\hat{\theta}) + 0.5$ (# of model parameters) log (sample size)] ($\mathscr{L}(\hat{\theta})$ is the predictive log-likelihood at convergence). The model with a lower BIC statistic is the preferred model. The BIC for the panel model is 6979.45, while the BIC for the constants only model is 7131.21, indicating, once again, that the panel model is the preferred model. In addition, we also computed the average probability of correct predictions for the two models, which returned a value of 0.192 for our model relative to 0.137 for the constants only model.

We also evaluated the performance of the two models at the aggregate level by comparing predictions at both the discrete share of participation (or not) in each WPL alternative as well as at the level of aggregate fractional splits. To conserve on space, we relegate the corresponding tables and matrices to an online supplement S. Suffice it to say that our model again clearly outperformed the constants-only model.

5. IMPLICATIONS

The estimation results in Sections 4.1 and 4.2 offer insights into the effects of exogenous variables on the baseline preferences and satiation parameters. But they do not provide an intuitive picture

of the effects of variables, and the relative magnitude of the effects of variables, on the actual days of work from each WPL. To do so, compute Average Treatment Effects (ATE effect; see Angrist and Imbens, 1991 and Heckman and Vytlacil, 2000), which is a general method to estimate the impact on a downstream posterior variable of interest (the number of days of participation in each WPL in our case) due to a treatment that alters the state of an antecedent variable (exogenous variable) from A to B. For example, if the intent is to estimate the "treatment" effect of distraction levels at the home office on WPL allocations, A can be the state where there is low distraction level when working from home, and B can be the state where there is high distraction level when working from home. The impact of this change in state is measured in terms of the change in the shares of the outcomes of interest between the case where all individuals in the dataset are in state A and the case where all the individuals in the dataset are in state B. This has the effect of holding all other exogenous variables fixed at those in the sample, so that the ATE can be viewed as the average change in WPL due to an individual being in state B rather than state A.

Note that the model can provide the WPL splits for any combination of the many exogenous variables. For example, just on the basis of the gendered lifecycle variables, there would be a total of 16 combinations for women (because of the interaction effects of variables involving the "female" variable with three age groups of children and whether or not living with a partner; see these effects appearing either in the baseline preference or satiation effects in Table 3) and four combinations for men (presence/absence of children over the age of 13 years and whether or not living with a partner), resulting in 20 gendered lifecycle variables that exhaust the population. In our ATE computations, we focus on just three of these combinations for presentation compactness:

1. Man with partner.

2. Woman with a young child 0-4 years (with no young children in other age categories) and with a live-in partner (simply "women with young child with partner" from here on).

3. Woman with a young child 0-4 years (with no young children in other age categories) and without a live-in partner ("labeled as "women with young children without partner").

We confine our ATE analysis to these three groupings (from the original 20) to focus on the lifecycle period that corresponds to having young children; this lifecycle period is known to be the most challenging for parents in terms of time availability (see, for example, Del Boca et al., 2020) Also, the presence or not of young children has no impact on a man's WPL choices, and the differences for men with a live-in partner or without was not too substantial in the lifecycle grouping. In addition to limiting to the three gendered lifecycle groupings just identified, for the ATE computations in this paper, we consider the case of only full-time work with 22 work days a month.[9] For each of the three gendered lifecycle categorizations, we undertake several single-variate analyses, and determine the WPL effects of several exogenous variables.

The results are presented in Tables 5 through 9. In Table 4, the third column presents the estimates of the WPL split of the 22 days per month for each gendered lifecycle group, assuming

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[9] An expanded set of ATEs corresponding to six gendered lifecycle categories and for full-time (=22 work days a month) as well as part-time (=11 work days a month) is available in an online supplement.

the distributions of all other variables are as in the full sample. That is, the model predicts that the desired average WPL split in the group of individuals who are men living with a partner would be 9.8 days from home, 11.4 days from the work office, and 0.7 days from a third WPL. On the other hand, for women with a young child and living without a partner, the split would be 19.9 days from home, 1.9 days from the work office, and 0.2 days from a third work place (see the last row panel of Table 4). The remaining columns of the table further breakdown the splits for each of the three gendered lifecycle categories by each additional exogenous variable. Thus, the fourth broad column provides the predicted splits by age groupings that indicates, for example, that for men living with a partner, the average WPL splits for those in the 18-29 year age group would be 10.5 days from home, 10.6 days from the work place, and 0.9 days from a third WPL. The last sub-column of the fourth broad column finally provides the percentage change in WPL splits going from the left extreme category (18-29 years, which serves as the base category) to the right extreme category (65 years or older, which serves as the treatment category). This corresponds to the ATE effect. Thus, the boldfaced value of **-15.2**% indicates that, in the group of men who are 65 years of age and living with a partner, one can expect that the average share of days working from home will be about 15% lower than in the group of men who are 18-29 years of age and living with a partner. Another way of interpreting this result is that a random male living with a partner who is 65 years of age will work from home about 15% fewer days per month than a random male living with a partner who is in the 18-29 years of age. All other numbers in Table 4 and the remaining tables may be similarly interpreted. We provide both the predicted splits by each sub-grouping (by age in the discussion above) as well as the ATE, because the ATE magnitude can be deceiving when the base split is low (this happens particularly for the third WPL alternative). The combination of the predicted splits and the ATE provide a more complete picture of WPL shifts due to each exogenous variable for each of the three gendered lifecycle categories.

The results generally follow the discussion in Sections 4.1 and 4.2, though we can now "see" the actual WPL split differences across different exogenous variable groupings, rather than simply the exogenous variable impacts on baseline preferences and satiation parameters. Besides, for some variables such as COVID risk, where there is an effect on both the baseline preferences of the WPLs as well as the satiation parameters, the net result on splits is more clearly identified through the predicted splits in this section. We discuss some of the salient observations from the tables, while also discussing implications under five broad topics: (1) Who are the ones who prefer more WPL hybridization?, (2) Geographic or environmental WPL attributes: which impacts hybridization preferences more?, (3) How should employers prepare for and design hybrid workplace structures?, (4) What are the implications for travel demand?, and (5) How to prepare for when a COVID-like pandemic strikes again?

5.1. Who are the Ones Who Prefer More WPL Hybridization?
Our results provide important insights about WPL hybridization preferences by demographics (see Table 4). Regardless of other exogenous characteristics, women would like to have a higher split of work days from home than men. This elevated desire to work from home is particularly acute

for single mothers with very young children, to the point where, regardless of other characteristics, such workers prefer working from home a staggering 19-20 days of the 22 days, with only 1-3 days from the work office and rarely from a third workplace. Overall, based on demographics, young women (18-29 years of age) living alone with young children and in the highest household income bracket have the highest preference for working from home. On the other hand, for the work office WPL, men older than 65 years in the lowest household income bracket have the highest preference. And, for the third WPL, it is the third demographic grouping of young women (18-29 years of age) with very young children, living with a partner, and with low household income who have the highest desire (as discussed earlier, presumably as a way of getting "protected" work time while also not having to go into the work office).

The results above can help cities and other regional entities understand and prepare for the desired mix of office and third WPL locations. We discuss these issues later in the context of travel demand and employer policies, but insights on the distribution of work locations can also be useful for city planners, developers, retailers, home builders, and restauranteurs in terms of strategic decision-making to achieve desired states. For example, home builders may want to design homes with a relatively good sound-proof study room to provide a distraction-free work environment as a means to increase home sales, especially in areas with a high fraction of young single mothers. Child care businesses may want to penetrate into traditionally residential areas, given the critical mass of home workers who may want to have focused work time without distraction from their young children. Nanny services may also benefit by providing customized child care services within the home. In terms of the third WPL remote arrangement, developers may want to site new affordable hotels and coffee shops to take advantage of the third WPL demand (that is, the so-called "digital nomad" demand) in locations populated by those with young children and in low-priced housing markets. In fact, the rising number of such digital nomads has already started redefining the functionality of several traditionally used leisure spaces such as summer cottages, resort towns and coffee shops that now also are serving as new temporary (or more stable) workplaces, and are extending to urban region cores. To put things in context, a study in 2018 by the consulting agency MBO Partners illustrated the rise of this particular nomadic lifestyle movement even before the pandemic; rough estimates indicate the presence 4.8 million digital nomads in the United States (MBO Partners, 2018) alone. The pandemic has further increased the number of such digital nomads (see Nanopoulos et al., 2021).

5.2. Geographic or Environmental Attributes: Which Impacts Hybridization Preferences More?

Table 5 indicates that commute time to the work office (a geographic/location WPL attribute) has the most impact for women, with work office instances reducing by 15.6% for women with young children living with a partner and by 25.4% for women with young children not living with a partner (see the third broad column of Table 5). The corresponding reduction for men living with a partner is only 7.3% (these reductions are for an increase in commute time from shorter than current by 50% to longer than current by 50%). For the third workplace, an increase in commute

time (from 50% of the current work office commute to the same as the work office commute) has the expected reduction in third WPL days of work between 7.8% to 12.4% away from the third work place, with again higher impact for women than men.

Moving on to the environmental WPL attribute of distraction levels, Table 6 reveals that distraction at the third WPL has the most adverse effect on working from there (almost a 50% drop in frequency; see the third sub-row of each row panel in the last column of Table 7). The corresponding decreases due to distraction effects at the home and work office are not as substantial, suggesting that distraction may be more easily worked through at home or in the work office with familiar co-workers. More generally, women appear to be more sensitive to distraction at the work office relative to distraction at home. For instance, for women with a young child living with a partner, higher distraction at home (relative to no distraction) leads to a frequency reduction of 13.5% of working from home, compared to a frequency reduction of 17.1% for work office frequency due to higher distraction at the work office (see the middle row panel of Table 6). But this switches over for men, who are more sensitive to distraction at home (-15.8%) relative to distraction at the work office (-11.6%). This is a novel finding of our study, because earlier studies have not adequately considered gendered variations by WPL (AM et al., 2022 find that women are more sensitive in general to noise-related distractions than men, but do not consider responsiveness to distractions based on specific WPLs).

It is admittedly challenging to compare the magnitude effects of commute times and distraction levels, as these variables are fundamentally different in nature (commute time is on a cardinal quantitative scale, while distraction level is on an ordinal qualitative scale). But, given the assumed change from the low extreme to the high extreme for each, we may make some general observations. For each of the three gendered lifecycle groups and for each of the work office and third WPL alternatives, the commute time effect is lower than the distraction level effect. For example, for men with a partner, an increase in work office commute leads to a 7.3% reduction in work office frequency, relative to a 11.6% reduction due to an increase in work office distraction level; for women with a partner, an increase in work office commute leads to a 15.6% reduction in work office frequency, relative to a 17.1% reduction due to an increase in work office distraction level. The difference in effects of commute time and distraction level is even more stark for the third WPL. For men with a partner, an increase in third WPL commute time leads to a 7.8% reduction in third WPL frequency, relative to a 50.8% reduction due to an increase in third WPL distraction level; for women with a partner, an increase in third WPL commute leads to a 12.2% reduction in third WPL frequency, relative to a 48.5% reduction due to an increase in third WPL distraction level. These results suggest that the environmental attribute of distraction level at WPL is more important than the geographic attribute of commute time to the WPL. This is especially so for men and for the third WPL. The results suggest that, to promote the work office WPL, corporate institutions may want to invest on reducing distraction in the environment of the work office (such as utilizing staggered work hour policies and/or dedicated cubicle set ups with some noise-proofing) at least as much (if not much more) than the location of their facility buildings.

5.3. How Should Employers Prepare for and Design Hybrid Workplace Structures?

For most employers, the question of how to retain employees has arisen amidst this period of the 'Great Resignation' or the 'Big Quit'. Therefore, there is a pressing need among employers to rethink their WPL-related policies so they are more congruent with the desires of their employees. The column labeled "Only Gendered Lifecycle Treatment (days)" in Table 4 displays the average split across the three alternatives based on only gendered lifecycle; with the exception of women with a young child and without a partner, all gendered lifecycles display an almost even split of days between working from home and from the work office (with an average of 9.0 days and 8.4 respectively). In fact, it is quite evident that the hybrid work structure is preferred for all gendered lifecycle categories, regardless of the sociodemographic, geographic- and location-based attributes of the three workplaces. Even in terms of job occupations (see Table 7), there is a clear desire for hybrid work arrangements, even if there are variations across the occupations. Indeed, as expected, respondents did consider their job occupations in providing their preferred WPL splits. Those in the essential services (health case/retail sales/education) recognize the importance of their in-person presence for societal functioning, reporting the highest split for work from the work office, while those in the information/finance, professional/managerial/technical, and public administration occupations express the highest preference for working remote.

Overall, it is clear that (1) employees are now used to and appreciate the value of WPL flexibility that COVID safety measures forcibly enabled during the last two years, (2) employees have been able to find a balance of their personal priorities and professional objectives by optimally allocating their time in a hybrid work arrangement, and (3) employees now expect their employers to provide them the flexibility of a hybrid arrangement given its social benefit. In this context, our results on WPL allocation patterns provide a valuable glimpse into employee WPL preferences into the future, which employers can use for future company planning, recruitment policies (such as, which sociodemographic subgroup to focus on based on work place resources) as well as possible investment strategy in both office spaces and office resources (such as furniture, technology, or other perks offered to work office employees).

Our results also recommend that employers not view future WPL arrangements as a "this or that" (only from work office or only remote) proposition. Indeed, arguments regarding in-person work office culture vs. remote work culture often tread on the extreme cases; for example, individuals promoting in-person work culture often argue about the benefits of professional interactions, unplanned communications, and "team mentality" development within co-workers to improve productivity. On the other hand, individuals who favor the remote work option often invoke considerations of increased flexibility, commute time savings, and social-environmental benefits. A hybrid work structure, on the other hand, helps harness the best of both worlds and the recent pandemic has, in a way, helped workers appreciate the benefits of such an arrangement. Employers and corporate institutions have little choice than to take a more open-minded stance toward a hybrid arrangement, so as to avoid any dissonance with workers. This is not simply in the context of allowing employees to work from home, but also to invest in facilities that may serve as third WPL options. Such investments may be in the form of company-owned facilities

that serve as a third WPL, or arrangements with food and hospitality providers (including coffee shops and hotels) for subsidized or even complimentary use by employees.

5.4. What are the Implications for Travel Demand?

Tables 5 and 8 reveal that there are variations in work hybridization preferences by sociodemographics and job-related characteristics. At the same time, the results point to the fact that work hybridization will be the norm as the job market adjusts to employee WPL preferences. Thus, it is imperative that work hybridization, and the variations in such patterns, be accounted for in travel demand modeling to avoid the ecological fallacy that originates from ignoring the effects of WPL heterogeneity on broader activity-travel patterns.

To be sure, there is a long history of literature focusing on work-related effects on broader activity-travel patterns of individuals. For example, many activity-based travel models use the work activity as a peg around which to "build" the remaining elements that make up the overall activity-travel pattern of an individual (for example, see Bhat et al., 2004 and Cambridge Systematics, 2021). But these studies focus on a single day of analysis, and so consider teleworking only in the context of a binary "switch" of whether or not an individual travels to the work office on a given day. However, it is critical today to consider hybrid work arrangements over longer periods of time, and its consequent impacts on activity-travel patterns. This, of course, raises a series of questions on how to "consummate" a longer term (such as a month-based) WPL split model with models that use a typical weekday as the unit of analysis. One simple approach would be to include the monthly WPL pattern (in the form of fractional splits of different WPLs) as an explanatory variable in the weekday-based modeling timeframe of current models. But this would not consider the intra-individual variations in activity-travel patterns across days. An alternative modeling approach would be to fundamentally change to a multi-day unit of analysis in travel demand modeling. For example, a recent effort by Haddad et al. (2022) uses the WPL monthly split as an exogenous variable to study evening dining frequency over the period of a month. These and related considerations offer intriguing new challenges, as the profession works toward adapting travel demand models to a new era of work arrangements.

Beyond travel demand models, hybrid WPL arrangements also can affect land-use patterns, as some employers may downsize their offices and have multiple smaller office sites spread over a metropolitan area. Or, as discussed earlier, employers may partner with hospitality and food providers to offer third WPLs to their employees. These types of land-use changes can then itself create new short-distance and spread-out commute patterns, whose implications on travel demand will need careful attention.

In summary, the important effects of hybrid work arrangements not only on peak traffic congestion, but also on land-use patterns and the broader activity-travel patterns of individuals, is critical to consider in travel demand modeling. In this regard, the estimated remote and non-remote monthly temporal split of different sociodemographic groups can serve as an input to several modules of land-use and travel demand models.

5.5. How to Prepare for When a COVID-like Pandemic Strikes Again?

There is significant uncertainty over how individual WPL decisions would change if there is a resurgence of the COVID pandemic, possibly through another mutated strain of the virus, or another similar society-disrupting pandemic. Such decisions would primarily depend on two factors: internal factors such as the individual's own perceived health and external factors such as how high is the risk. To evaluate future WPL preferences under such circumstances, we consider a set of COVID-related ATEs, presented in Table 8.

Regarding the gendered lifecycles, Table 8 shows that the group of women with young children and without a partner is most likely to reduce their work office instances when they or someone they frequently see is immunocompromised (29.4% reduction in days away from the work office when the employee is immunocompromised, and 25.2% shift away when the employee comes in frequent contact with someone immunocompromised). An interesting observation across all gendered lifecycles is that the shift toward a third workplace is higher than the corresponding shift towards the home office when immunocompromised. This demonstrates that, in a continuing COVID environment, being immunocompromised toward COVID is something individuals have begun to learn to live with; hence, these individuals do not intend to remain sheltered at home and instead work at a third workplace, in order to break free from the monotonous lifecycle of "safely" working from home. This is perhaps also a reflection of the psychological distress that workers experienced while being continuously "locked" at home for months during the COVID pandemic. The implication is that there is added value not just today, but for the future, for employers who invest in facilities that may serve as third WPL options.

The preference trend of employees appears to be somewhat different when the threat concerns the entire society, as is the case for overall COVID risk. In both cases of when the COVID risk is deemed high and unknown, relative to no threat, there is, as one would expect, an evident shift away from both the in-person work office and the third workplace (and toward working from home; see the last column of Table 8). But, there is a difference in the magnitude pattern of WPL changes between the two cases. When the COVID risk is high, the percentage shifts are of about the same magnitude (20-28%) for the three WPLs (except, of course, for women living alone with very young children who have large percentage shifts for the work office and third WPL, but these really are due to the small base preference for the non-home WPLs in this population group). But when the COVID risk is unknown, the percentage reduction in the third WPL dwarfs the percentage changes for the other two WPLs. This is primarily because, when the COVID risk is unknown, the public is more circumspect about third-workplace locations where the environment is beyond one's control (in terms of COVID-appropriate behavior) compared to a home or a work office (where stricter protocols are likely to be maintained). This brings out a basic issue about human nature that has been well established in the social-psychological literature (see, for example, Wu et al., 2021). Humans, when in situations where they know they have to compromise on individual preferences (such as at a third WPL, where they know they will be in the midst of strangers), prefer having uniform protocols of engagement (as is likely to be the case when the

COVID risk is high) than not having uniform protocols (as would be the case when the COVID risk is unknown, which can lead to angst-raising variations across individuals in safety behavior.

6. CONCLUSIONS

In this paper, we have examined WPL preferences of workers in an unpredictable and evolving post-COVID future by investigating how workers would prefer to allocate their monthly working days among the three WPL alternatives of working from home, from the work office, and from a variable third WPL. The novelty of our approach is that, for the first time to our knowledge, we recognize that the three work location arrangements may not be perfect substitutes of each other, but satisfy different functional, social, productivity, emotional, privacy, visibility, networking, financial and other personal/professional objectives to varying extents. Thus, in contrast to earlier studies that typically focus on telework as a binary of whether an individual is a teleworker or not, we focus our attention on workers' preferences for specific combinations of all three WPLs over a period of a month (including, but not limited to, only selecting one WPL for all days of the month).

The study employed a traditional MDCEV model (Bhat, 2008) to investigate the allocation of the total number of work days of the individual among various different combinations of WPLs. The data used for the analysis is drawn from a 2022 stated preference survey of future work preferences of workers. Respondents were asked to provide their optimal WPL arrangement, assuming full discretion in the choice. The responses, collected from residents of the state of Texas, were then related to geographic and environmental WPL correlates, job-related attributes, and COVID threat.

The results from our model indicate that single young women with very young children, those with long commutes and "intolerable" traffic congestion to the work office, individuals with a private study in their homes, self-employed workers, and those in non-essential service occupations have the highest preference for working from home. On the other hand, older men, individuals from low income households, those residing in rural areas, and workers in essential service occupations have the highest preference for the work office. And, for the third WPL, young non-single women with very young children, individuals from low income households, part-time employees, and those in professional, managerial or finance occupations have the highest predisposition. These results should provide valuable insights to urban planners, homebuilders, employers, travel demand modelers, and a whole host of other businesses to achieve desired end states.

Our results also point to the immediate work environment being at least as important (if not more important) than geographic WPL location attributes such as commute time, with the recommendation that corporate institutions invest more on ways to reduce distraction in the environment of the work office if they plan to encourage employees to work from the office too at times for organizational productivity. Also, steering an employee toward or away from a certain WPL option will be heavily influenced by the people and safety protocols inside a workplace. Overall, our study can inform policies directed toward engendering an optimal work environment

customized to individual desires as well as organizational needs. From a data collection standpoint, our study underscores the need to collect much more detailed information in activity-travel surveys about work patterns, including typical work hours on working days, variations in work hours across work days, weekly number of work hours, and the monthly number of work days (rather than a simple part-time versus full-time categorization based on number of work hours per week).

Of course, as with any paper, there are several directions for future research. While this study considered a host of demographic, job, WPL, and COVID threat characteristics, it did not consider the specific type of activities that individuals pursue on their job nor did it consider employees' subjective valuations of mental and social wellbeing, productivity, and control as they impact WPL choices. Including such social context factors, possibly through latent attitudinal constructs estimated through the collection of a batter of indicator variables, can provide additional insights into hybrid work patterns. Further, while the sample size for this study was reasonable (1,136 respondents, each of whom provided responses to two SP choice occasions), a larger sample size in future studies may unravel further interactions among variables that could not be teased out in the current study.

To conclude, as the effects of COVID-era on society continue to wane, it will be interesting to see how society adjusts to returning to various physical environments. Our study provides what we believe is a solid foundation in this direction in the specific context of WPL choices, though much more about our activity-travel patterns and our very ways of life remain to be explored, leaving open a challenging and exciting time for human behavioral research as we continue into an uncertain and unprecedented future.

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Table 1: Experimental Design Attribute and Levels

Work from Home		
Distraction Level		
• High distraction • Low distraction • No distractions		

Work from the Work Office		
Distraction/Crowding Level	**Commute Time**	**Workplace Safety Implementation for COVID**
• No crowding at the out-of-home workplace; you have your own designated, quiet, closed-off room (No distractions) • Some crowding at the out-of-home workplace, but you have a small area to yourself or with chosen coworkers (Low distraction) • The out-of-home workplace is crowded and you are in close proximity to quiet coworkers (Low distraction) • The out-of-home workplace is crowded and you are in close proximity to loud coworkers (High distraction)	• Same commute length as before • 50% longer than before • 75% longer than before • 50% shorter than before • 75% shorter than before	• No safety regulations • Only one safety measure is implemented • Two or more safety measures are implemented

Work from a 3rd WPL	
Distraction/Crowding Level	**Commute Time**
• No crowding at the third workplace; you have your own designated, quiet, closed-off room (No distraction) • Some crowding at the third workplace, but you have a small area to yourself or with chosen coworkers (Low distraction) • The third workplace is crowded and you are in close proximity to quiet strangers (Low distraction) • The third workplace is crowded and you are in close proximity to loud strangers (High distraction)	• Shorter than your outside-of-home workplace commute • Same length as your outside-of-home commute to the workplace

General Attributes		
COVID Risk Level	**Shifting Work Hours**	**Splitting Work Hours**
• There is a new strand of the virus and current vaccines are ineffective. Risk for the new strand is HIGH. • Both the vaccine's effectiveness against all current strands, and the % of people vaccinated are unknown. Risk is unknown. • 60% of people are vaccinated and the vaccine is effective for all current strands. Risk is low. • 80% of people are vaccinated and the vaccine is effective for all current strands. Risk is extremely low.	• Allowed • Not allowed	• Allowed • Not allowed

COVID Risk Level	60% of people are vaccinated and the vaccine is effective for all current strands. Risk is low.		
Attributes	*Work from Home*	*Work from the Workplace*	*Work from a 3rd Workplace*
Distraction level	Low distraction	Low distraction	High distraction
Commute time	-	7.5 minutes longer than before	Shorter than your out-of-home workplace commute
Level of crowding	-	The out-of-home workplace is crowded and you are in close proximity to quiet coworkers	The third workplace is crowded and you are in close proximity to loud strangers
Workplace safety implementation for COVID	-	Only one safety measure is implemented	-
Splitting Work Hour	Allowed	Not allowed	Allowed
Shifting Work Hours	Allowed	Not allowed	Allowed

You reported to work 22 days last month. For this scenario, please distribute the number of days you would work at each workplace so that they all add up to 22 . You can put 0 days for one or two of the alternatives as long as it adds up to 22 .

Remember, a third workplace is a remote workplace outside of the home such as a coffee shop, cafe, hotel, or co-working space.

Work from home	0
Work from the workplace	0
Work from a 3rd workplace (teleworking from a location that is not your home)	0
Total	22

Figure 1: Example SP Question

Table 2: Descriptive Statistics of WPL Participation and Frequency of WPL Participation

WPL Location	Total number (%) of choice occasions with positive participation[10]	Mean number of days conditional on positive participation	Number of choice occasions (% of total number of participations in each WPL location) with participation….[11]			
Home	1635 (72.0)	14.5	**Only in home**	**Only in home and work office**	**Only in home and third WPL**	**All WPLs**
			599 (36.6%)	771 (47.2%)	83 (5.1%)	182 (11.1%)
Work Office	1561 (68.7)	14.5	**Only in work office**	**Only in work office and home**	**Only in work office and third WPL**	**All WPLs**
			572 (36.6%)	771 (49.4%)	36 (2.3%)	182 (11.7%)
Third WPL	330 (14.5)	6.9	**Only in third WPL**	**Only in third WPL and home**	**Only in third WPL and work office**	**All WPLs**
			29 (8.8%)	83 (25.1%)	36 (10.9%)	182 (55.2%)

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[10] Percentages across rows in this column sum to more than 100% because of hybrid WPL configurations.

[11] Percentages sum to 100% for each row across the four sub-columns below, since the percentages are with respect to the total number of choice occasions with positive participation in each WPL (the second column in the table).

Table 3: Estimation Results

Exogenous Variables (base category)	Work from Home		Work from the Work Office		Work from a Third WPL	
	Coeff.	t-stat[12]	Coeff.	t-stat	Coeff.	t-stat
Individual and household-level Characteristics						
Gendered lifecycle variables						
Female	--		-0.178	-1.44	--	
Female * Child(ren) aged 0 to 4 years * Does not live with partner	2.742	2.44	--		--	
Female * Child(ren) aged 0 to 4 years * Lives with partner	--		--		0.466	1.60
Lives with partner	--		--		-0.320	-2.43
Presence of child(ren) 13 to 17 years	--		--		0.363	2.17
Age (18 to 30 years old)						
30 to 64 years old	--		0.550	2.42	--	
65 and older	--		0.590	2.20	-0.284	-1.35
Household Income (<$100,000)						
$100,000 to $249,999	--		-0.480	-4.79	--	
≥$250,000	--		-0.459	-3.14	-0.455	-2.16
Geographic WPL Attributes						
Commute Time						
Commute time	NA		-0.746	-2.67	-0.746	-2.67
Commute time * Female	NA		-0.591	-1.69	-0.591	-1.69
Commute Congestion Level to the work office (congestion is tolerable)						
Congestion to the workplace is intolerable	--		-0.311	-3.91	--	
Employment Density of the work office (medium-to-low)						
High	--		-0.396	-4.11	--	
Population Density of the residence (rural)						
Suburban	--		-0.659	-6.00	-0.469	-2.87
Urban	--		-0.969	-7.57	-0.469	-2.87
Environment WPL Attributes						
Distraction Level (low)						
Medium	-0.137	-1.46	--	--	-0.581	-3.81
High	-0.702	-2.26	--	--	-0.753	-4.79
High * 30 years or older	0.337	1.07	--	--	--	--
Medium * Younger than 30 years * Male	--	--	-0.314	-2.30	--	--
High * Male	--	--	-0.314	-2.30	--	--
(Medium/High) * Female	--	--	-0.398	-3.93	--	--
Home Ownership Status (rent)						
Own their home	--		0.189	1.63	--	
Household Characteristics						
Private Study	0.529	5.81	--		--	
Job-Related Attributes						
# Days Worked per Month (25 days or more (over time))						
1 to 5 days	--		-0.865	-3.42	-1.060	-1.89

	Est.	t	Est.	t	Est.	t
6 to 19 days	--		-0.210	-1.13	-0.491	-1.72
20 to 24 days (full time)	--		-0.220	-1.92	-0.382	-2.14
Employment Status (employed full-time)						
Employed part-time	--		--		0.880	4.49
Employment Structure (not self-employed)						
Self-employed	--		-0.275	-2.14	--	
Occupation (professional/managerial/technical job)						
Healthcare	--		0.715	4.08	--	
Retail sales/Food services	--		0.740	1.96	--	
Education/Social service	-0.492	-4.94	--		-0.692	-4.61
Public Administration	--		-0.499	-3.11	--	
Information/Finance	1.063	6.89	--		0.726	3.16
Shifting Work Hours (not allowed)						
Allowed * Female	--		--		0.280	2.16
Allowed * Children present in household	-0.225	-2.05	--		--	
COVID-19 Threat						
Immunocompromised Complications (self and others are not immunocompromised)						
Individual is immunocompromised	--		-0.416	-3.85	--	
Someone frequently seen is immunocompromised	--		-0.180	-1.76	--	
COVID-19 Risk Level (risk is extremely low or low)						
Risk is high	0.345	3.02	--		--	
Risk is unknown	0.765	4.72	0.527	3.24	--	
Baseline Preference Constant	NA		1.330	4.60	-0.391	-1.49
Satiation Parameter Estimates						
Individual-level Characteristics						
Gender (male)						
Female * Child(ren) aged 12 years or younger * Lives with partner	--		-0.556	-2.64	--	
Female * Child(ren) aged 13 years or older * Lives with partner	--		1.294	2.58	--	
Age (18 to 30 years old)						
30 to 64 years old	0.617	2.60	--		0.761	3.08
65 and older	0.617	2.60	0.550	2.05	0.739	1.98
Household-level Characteristics						
Income (<$100,000)						
≥$100,000	-0.324	-2.46	--		-0.552	-2.73
Job-Related Attributes						
Employment Structure (not self-employed)						
Self-employed	--		0.849	3.06	--	
COVID-19 Threat						
Immunocompromised Complications (self and others are not immunocompromised)						
Someone frequently seen is immunocompromised	--		-0.441	-2.90	--	
COVID-19 Risk Level (risk is extremely low or low)						
Risk is high	0.547	3.11	--		--	
Satiation Constant	1.604	6.85	2.427	18.97	1.340	6.69

Table 4: Sociodemographic ATEs

Gendered Lifecycle	WPL	Only Gendered Lifecycle Treatment (days)	Attribute Levels Alternative split (days) — Age (years)			Overall % change 18 to 29 to 65 and older	Attribute Levels Alternative split (days) — Income			Overall % change < $100K to ≥ $250K
			18 to 29	30 to 64	65 and older		<$100K	$100 to $250K	≥ $250K	
Men with partner	Home	9.8	10.5	9.9	8.9	**-15.2%**	9.0	10.3	10.4	**15.2%**
	Work Office	11.4	10.6	11.3	12.6	**18.8%**	To	10.9	11.1	**-9.2%**
	Third WPL	0.7	0.9	0.8	0.5	**-43.7%**	0.8	0.8	0.5	**-31.2%**
Women with young child with partner	Home	11.6	11.9	11.7	10.8	**-9.3%**	10.8	12.0	12.3	**13.4%**
	Work Office	8.8	8.3	8.6	10.1	**21.8%**	9.5	8.3	8.6	**-9.7%**
	Third WPL	1.6	1.8	1.7	1.1	**-38.2%**	1.7	1.7	1.1	**-31.4%**
Women with young child without partner	Home	19.9	20.0	20.0	19.7	**-1.4%**	19.7	20.1	20.2	**2.5%**
	Work Office	1.9	1.8	1.8	2.2	**21.8%**	2.1	1.7	1.7	**-19.4%**
	Third WPL	0.2	0.3	0.2	0.2	**-40.0%**	0.2	0.2	0.1	**-37.3%**

Table 5: Commute Time ATEs

Gendered Lifecycle	WPL	Attribute Levels Alternative split (days) — Work Office Commute Time (minutes)			Overall % change 50% shorter to 50% longer	Attribute Levels Alternative split (days) — Third WPL Commute Time (minutes)		Overall % change Short to Same
		50% shorter (13.2)	Average (26.4)	50% longer (39.6)		50% shorter than comm. to IP WP	Same as comm. to IP WP	
Men with partner	Home	9.5	9.9	10.3	**8.3%**	9.8	9.8	**0.3%**
	Work Office	11.8	11.4	10.9	**-7.3%**	11.4	11.4	**0.3%**
	Third WPL	0.7	0.8	0.8	**9.9%**	0.8	0.7	**-7.8%**
Women with young child with partner	Home	11.1	11.7	12.3	**11.3%**	11.5	11.6	**1.1%**
	Work Office	9.4	8.6	7.9	**-15.6%**	8.8	8.8	**0.9%**
	Third WPL	1.6	1.7	1.8	**13.6%**	1.7	1.5	**-12.2%**
Women with young child without partner	Home	19.8	20.1	20.3	**2.5%**	19.9	20.0	**0.1%**
	Work Office	2.0	1.7	1.5	**-25.4%**	1.9	1.9	**0.1%**
	Third WPL	0.2	0.2	0.2	**4.0%**	0.2	0.2	**-12.4%**

Table 6: Distraction Level ATEs

Gendered Lifecycle	WPL	Attribute Levels Alternative split (days) Distraction Level Home			Overall % change No to High	Attribute Levels Alternative split (days) Distraction Level Work Office			Overall % change No to High	Attribute Levels Alternative split (days) Distraction Level Third WPL			Overall % change No to High
		No	Low	High		No	Low	High		No	Low	High	
Men with partner	Home	10.6	10.0	8.9	**-15.8%**	9.5	10.7	10.7	**13.3%**	9.7	9.9	9.9	**2.5%**
	Work Office	10.7	11.3	12.3	**14.4%**	11.8	10.4	10.4	**-11.6%**	11.3	11.5	11.6	**2.2%**
	Third WPL	0.7	0.7	0.8	**19.5%**	0.7	0.8	0.8	**16.0%**	1.0	0.6	0.5	**-50.8%**
Women with young child with partner	Home	12.4	11.8	10.7	**-13.5%**	10.9	12.3	12.3	**12.9%**	11.3	11.8	11.9	**5.1%**
	Work Office	8.2	8.7	9.5	**16.6%**	9.6	8.0	8.0	**-17.1%**	8.6	9.0	9.0	**5.0%**
	Third WPL	1.5	1.6	1.8	**21.4%**	1.5	1.7	1.7	**16.1%**	2.1	1.2	1.1	**-48.5%**
Women with young child without partner	Home	20.2	20.0	19.6	**-3.2%**	19.7	20.2	20.2	**3.0%**	19.9	20.0	20.0	**0.6%**
	Work Office	1.6	1.8	2.2	**36.5%**	2.1	1.5	1.5	**-27.9%**	1.8	1.9	1.9	**0.9%**
	Third WPL	0.2	0.2	0.2	**40.7%**	0.2	0.2	0.2	**4.9%**	0.3	0.2	0.1	**-52.3%**

Table 7: Occupation ATEs

Gendered Lifecycle	WPL	Attribute Levels Alternative split (days) Occupation					
		Healthcare	Retail Sales/ Food Services	Education	Public Administration	Information/ Finance	Professional/ Managerial/ Technical job
Men with partner	Home	7.3	7.2	8.3	12.3	14.6	10.2
	Work Office	14.1	14.2	13.2	8.6	6.4	10.9
	Third WPL	0.6	0.6	0.6	1.1	1.0	0.9
Women with young child with partner	Home	9.3	9.2	10.3	13.6	15.7	12.0
	Work Office	11.3	11.4	10.4	6.2	4.4	8.2
	Third WPL	1.4	1.4	1.3	2.2	1.9	1.9
Women with young child without partner	Home	19.0	19.0	19.5	20.8	21.2	20.2
	Work Office	2.8	2.8	2.3	1.0	0.6	1.5
	Third WPL	0.2	0.2	0.2	0.2	0.2	0.2

Table 8: Covid Risk ATEs

Gendered Lifecycle	WPL	Attribute Levels Alternative split (days) — Immunocompromised (IC) Complications				Overall % change — Indv. is not to is IC	Overall % change — Other is not to is IC	Attribute Levels Alternative split (days) — COVID Risk			Overall % change — None to High	Overall % change — None to Unknown
		Indv. is not IC	Indv. is IC	Other is not IC	Other is IC			None	High	Unknown		
Men with partner	Home	9.53	11.20	9.23	10.80	17.5%	17.1%	8.87	11.56	10.06	30.3%	13.4%
	Work Office	11.74	9.92	12.08	10.36	-15.5%	-14.3%	12.22	9.76	11.44	-20.1%	-6.4%
	Third WPL	0.72	0.88	0.69	0.84	21.2%	21.3%	0.91	0.68	0.50	-25.5%	-45.2%
Women with young child with partner	Home	11.33	12.77	11.03	12.49	12.7%	13.3%	10.57	13.27	11.99	25.5%	13.4%
	Work Office	9.09	7.41	9.45	7.73	-18.5%	-18.2%	9.47	7.32	8.91	-22.7%	-5.8%
	Third WPL	1.57	1.82	1.52	1.78	15.8%	16.7%	1.96	1.42	1.10	-27.7%	-44.0%
Women with young child without partner	Home	19.85	20.41	19.76	20.27	2.8%	2.6%	19.57	20.58	20.07	5.2%	2.6%
	Work Office	1.95	1.38	2.04	1.52	-29.4%	-25.2%	2.17	1.27	1.80	-41.2%	-16.9%
	Third WPL	0.20	0.21	0.20	0.21	4.6%	4.2%	0.27	0.15	0.13	-43.9%	-51.4%